LITERATURE REVIEW FOR APPLICATION OF FAULT DETECTION AND DIAGNOSTIC METHODS TO VAPOR COMPRESSION COOLING EQUIPMENT

Sponsored by
ASHRAE
Deliverable for Research Project 1043-RP
Fault Detection and Diagnostic (FDD)
Requirements and Evaluation Tools for Chillers

HL 99-19 Report #4036-2

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DECEMBER 1999

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1.0 Introduction

1.1 Objectives

Although there is a large body of literature on fault detection and diagnostics (FDD) for applications in critical processes, relatively little exists for application to chillers or other vapor compression equipment. However, as the cost of hardware (e.g., sensors, micro-processors) has gone down, interest in FDD systems for chillers has grown. The overall objective of this document is to provide an up-to-date review of literature related to FDD for chillers. The review includes papers describing chiller applications and other HVAC&R equipment applications with cost and performance requirements similar to those for chillers. In addition to describing FDD methods, the review addresses studies that survey common faults or provide tools or data that may be useful in the development of FDD methods for chillers.

1.2 Sources

The FDD papers were taken from many sources, including ASHRAE Transactions, ASHRAE Journal, International Journal of HVAC&R Research, IEEE Transactions, Automatica, publications of the IEA Annex 25, and graduate theses. Although the primary goal was to identify papers on FDD methods applied to vapor compression equipment, papers on this topic have only started to appear within the past five years. Thus, it was easy to identify these papers. In addition, papers commonly found in the reference lists of recent FDD papers were reviewed in order to provide the proper background. Older surveys such as Willsky (1976), Isermann (1984), Frank (1987), and Gertler (1988) are also included for completeness.

1.3 Organization

The main body of the report is organized in three sections: FDD methods, survey papers, and FDD tools and data. The FDD methods section contains reviews of papers that describe complete FDD methods that have been developed and at least partially evaluated. The papers are further organized within this section according to application: chillers, packaged air-conditioning equipment, other HVAC&R systems and subsystems, and generic applications. The section on survey papers describes papers that attempt to present general features and organization of FDD methods. The FDD tools and data section includes information that could be useful in the development of FDD methods such as descriptions of fault surveys, data on the impacts of faults on performance, and analysis tools or partial FDD methods.

Each paper within the FDD methods section was reviewed using the following organization:

1. **Overview**
   Similar to an abstract except it emphasizes the application and the faults that were introduced. Papers that do not present an FDD method or do not apply it to a specific application only include the overview section.
2. **FDD Method**
   Describes the model (fuzzy logic, neural network, statistical rules, etc.), the means by which faults are classified, and lists the relevant measurements necessary to implement the method.
3. **FDD Evaluation**
   Explains the nature of the simulation and any laboratory or field-tests that were performed in the evaluation of the FDD method. Provides detailed explanations of the faults that were introduced.
4. **FDD Results**
   Presents any results contained in the paper, including the sensitivity and the false alarm rate if they were calculated. This is normally the last section.
5. **Method Assessment**
   An optional section—assessing the applicability of the method to an HVAC system if no application was made or posing some further questions about the method's development.

1.4 Overview of Papers Related to FDD for Vapor Compression Equipment

1.4.1 Fault Repair Frequency and Costs

Very little literature is available that addresses the causes of system failures or other needs for service of air conditioning equipment. Stouppe and Lau (1989) performed the most comprehensive study. They summarized the cause of 15,716 failures that led to insurance claims in HVAC&R equipment over an eight-year period from 1980 to 1987. Of the failures in hermetic air conditioning units; 76% were attributed to electrical components, 19% to mechanical components, and 5% to items in the refrigeration circuit. Of the electrical failures, almost 87% were failures in the motor windings. The primary causes given for motor failure were deterioration of the insulation, unbalanced or single-phase operation, short cycling, and refrigerant contamination. The mechanical failures were almost all in the compressor valves, bearings, or connecting rods. The primary reasons given for these failures were general fatigue in the valves and valve springs, liquid slugging, and a loss of lubrication.

More recently, Breuker and Braun (1998a) presented results from an analysis of a database of service records for a HVAC service company that specializes in equipment for large commercial retail chain stores. Most of the stores use direct expansion rooftop air conditioning units. The entire database contained over 6000 separate repair cases from 1989 to 1995 and included repairs resulting from component failures, comfort complaints, and regular maintenance. The repairs were analyzed in terms of both frequency of occurrence and total cost of repairs. Of the faults that led to inadequate comfort conditions, approximately 60% were related to electrical and control failures, while mechanical problems accounted for about 40%. Although compressor failures only accounted for about 5% of the service calls, they were by far the most costly failure for unitary air conditioners, representing about 25% of the total service costs within the database analyzed in Breuker and Braun (1998a).

Breuker and Braun (1998a) also did some analysis of the causes that lead to compressor failures through interactions with industry personnel. It was found that although most failures in hermetic compressors are diagnosed as a failure in the motor, these failures are usually the result of a mechanical problem that overloads the motor and leads to failure. Furthermore, the primary cause of mechanical failures in positive displacement compressors is liquid refrigerant in the compressor. Some causes of liquid floodback to the compressor are fouled evaporator coils, fouled condenser coils, refrigerant overcharge, and a faulty thermal expansion valve (TXV). Other conditions that lead to early compressor failure include high compressor temperatures and electrical supply problems, such as low voltage and voltage spikes. High compressor temperatures are caused by a condenser fan failure, condenser fouling, liquid line restriction, or low refrigerant charge. In addition to leading to premature compressor failure, faults associated with refrigerant leakage, the evaporator, and the condenser accounted for about 20% of the total service costs.

1.4.2 Fault Testing and Performance Impacts

The previous FDD studies on vapor compression equipment involved the artificial introduction of faults in a laboratory setting. In order to quantify the performance of any FDD technique, it is necessary to characterize the fault level introduced. Different approaches have been followed for both introducing and characterizing faults.

In general, refrigerant loss has been introduced through a controlled discharge of a fixed amount of refrigerant into a receiving vessel. The level of refrigerant loss is easily quantified by weighing the vessel before and after the discharge.

A liquid-line restriction (clogged liquid line dryer or expansion device) has been introduced by closing a valve located before the expansion device. In this case, the fault level has been characterized in many different ways, including valve position, a reduction in flow area (Rossi and Braun, 1997), a reduction in mass flow rate (Stylianou and Nikanpour, 1996) or an increase in the overall pressure differential between the condenser and evaporator (Breuker and Braun, 1998a). Although the first two measurements are easy to obtain, they result in non-linear relationships between fault level and the performance indices used for FDD (e.g., refrigerant temperatures). The second two fault characterizations require measurements for both fault and no-fault cases at each operating condition, but are better indicators of the fault's impact.

For water-cooled chillers, Grimmelius et al. (1995) and Stylianou and Nikanpour (1996) experimentally simulated condenser and evaporator fouling by reducing water flow rates. Similarly, Rossi and Braun (1997) introduced fouling of the condenser of a rooftop air conditioner through reductions in airflow rate. In each of these cases, the fault levels were characterized in terms of a reduction in flow rate.

Breuker and Braun (1998a) recognized that heat exchanger fouling and a loss of secondary fluid flow (air or water flow) are two different types of faults with different impacts on system performance. For instance, a build-up of debris on the face of an air-cooled condenser coil causes a net loss of condenser surface area available for heat transfer and can lead to a reduction in the air temperature difference across the coil. However, a problem with a condenser fan can cause a reduction in the airflow rate that leads to an increase in the air temperature difference. In rooftop tests, Breuker and Braun (1998a) introduced condenser fouling by blocking the condenser face with uniformly spaced, vertical strips of paper and characterized the fault level as a reduction in the exposed face area. On the evaporator side, a plugged air filter was experimentally simulated and characterized through a decrease in airflow rate. Similar arguments could be made for the difference in impacts of scale buildup and water flow reduction for the condenser or evaporator of a water-cooled chiller. Each of these faults needs to be introduced separately to generate data that is useful for the development and evaluation of FDD methods.

There are a variety of faults that can affect a compressor's cooling capacity and power requirements. Cooling capacity is degraded when the compressor provides less refrigerant flow than expected at a given operating condition. Flow losses may be due to refrigerant leakage from high pressure to low pressure regions within a positive displacement compressor (e.g., across suction or discharge valves or between adjacent compression chambers), a loss in aerodynamic performance of a centrifugal compressor due to impeller wear, heating of refrigerant during the compression process due to frictional losses or within the shell of a hermetic compressor due to motor losses, or a reduction in compressor speed due to mechanical, electrical or control problems. These losses are related to wear, which may be accelerated through conditions where the entering refrigerant contains liquid or is highly superheated.

In previous studies by Rossi and Braun (1997) and Breuker (1997), compressor flow losses for a reciprocating compressor were experimentally simulated using a bypass valve that allowed gas from the discharge line to recycle into the suction line. The fault level was quantified in terms of a reduction in the refrigerant flow rate as compared with the no-fault condition. This approach to simulating flow losses is only appropriate for representing leakage from high to low pressure within the compressor. Furthermore, it does not address faults that affect power consumption, but have little impact on cooling capacity.

A few studies have addressed the effects of faults on overall air conditioning system performance. Bultman et al. (1993) showed a 7.6% decrease in system COP for a 40% reduction in airflow for an air conditioner. Krafthefer et al. (1987) estimated a 10-13% decrease in the COP for typical evaporator filter fouling of a heat pump. Furthermore, they estimated operating cost savings of 10-25% through use of a high efficiency air filter upstream of the evaporator. Rossi and Braun (1996) compared the combined service and energy costs associated with optimal maintenance scheduling for cleaning of condensers and evaporator air filters for rooftop air conditioners. They estimated total cost savings between 5 and 15% compared with periodic maintenance practices. The most comprehensive experimental study of the effect of fault levels on performance was reported by Breuker and Braun (1998a). They quantified the impact of five faults on a variety of refrigerant and air states for a rooftop air conditioner during both transient and steady state operation at a range of fault levels and operating conditions. They also evaluated changes in cooling capacity, COP, superheat at the compressor inlet, and the compressor discharge temperature due to the five faults. Capacity and COP provide a means of comparing the impact of different faults and quantifying the level at which faults become important.

1.4.3 Background on FDD Methods

There is a wealth of literature related to FDD for critical processes, such as aircraft engines or production-related processes, such as those that exist within chemical process plants. Many authors (Willsky 1976, Isermann 1984, Frank 1987, Basseville 1988, Gertler 1988, Frank 1990) have offered excellent review papers on fault detection and diagnostic methods that were developed for these types of applications.

Isermann (1984) presents the application of FDD techniques as a series of four steps termed "process supervision," which is a good reference model for describing many of the FDD methods that have been developed for cooling equipment. Figure 1.1 shows the four-step process applied to HVAC equipment. The first step is fault detection, in which a fault is indicated when the performance of a monitored system has deviated from expectation. The second step, diagnosis, determines which malfunctioning component is causing the fault. Following diagnosis, fault evaluation assesses the impact of the fault on system performance. Finally, a decision is made on how to react to the fault. This is usually a choice between tolerating the fault, repairing it as soon as possible, adapting the control, and stopping operation until repair is complete.

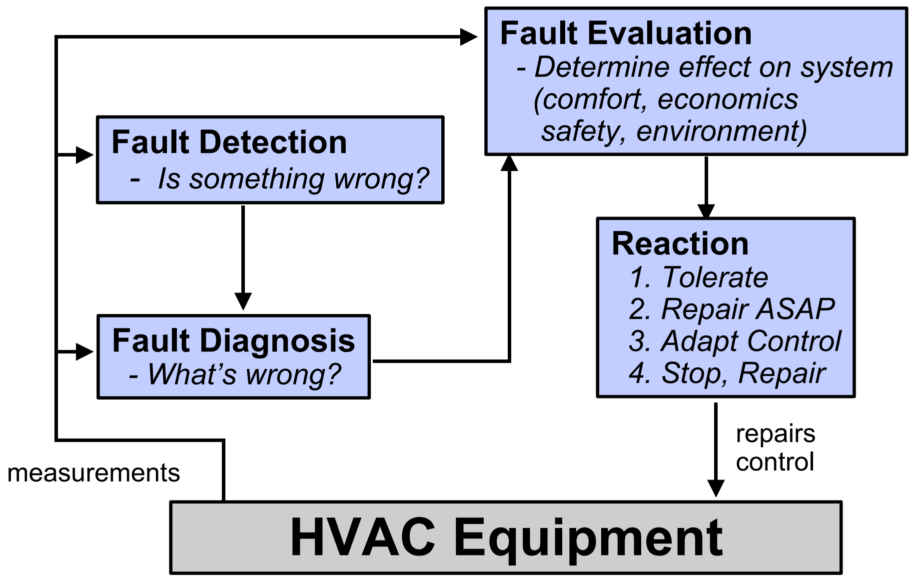

Figure 1.1 Supervision of HVAC&R Equipment

In each of these steps, it is necessary to define criteria or thresholds for establishing appropriate outputs. The outputs would be fault or no fault for fault detection, the type of fault for diagnosis, and repair or don't repair for the fault evaluation step. In some methods, fault detection and diagnostics are combined into one step. In this case, the diagnostic tool includes "normal operation" as one of the outputs in addition to all of the fault possibilities.

Fault Detection

Fault detection is accomplished by comparing performance determined from measurements with some expectation of performance. If the deviation exceeds a threshold, then a fault is indicated. Often this process is divided into two steps as depicted in Figure 1.2: preprocessing and classification. The preprocessor takes measurements from sensors and manipulates them to generate features for classification. Classifiers then operate on the features to determine whether the system contains a fault.

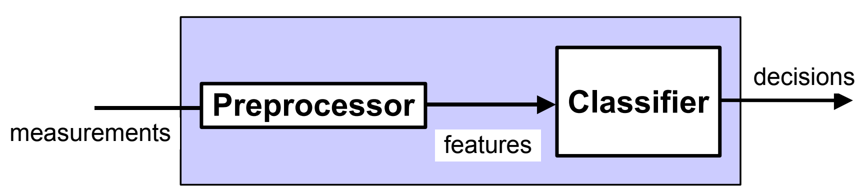

Figure 1.2 Sequential Steps in Fault Detection and Diagnosis

Simple transformations, characteristic quantities, and models are three types of preprocessors that have been employed. Simple transformations involve manipulations of the raw data, such as trend generation (i.e., time derivatives). Characteristic quantities are features that are computed directly from measurements and are indicative of component performance. Examples include overall system efficiencies and heat exchanger effectiveness. Model-based preprocessors utilize mathematical models of the monitored system to generate features. Model parameters could be learned from measurements when the system is operating normally, or determined using physical models. Model-based preprocessors can be categorized in terms of the types of performance indices generated for classification, the structure the model, and the types of dynamics considered as follows:

Model-based preprocessor

Performance indices generated by model-based transforms

- Innovations
- Physical parameters
- Characteristic quantities

Process model structure

- Physical models
- Black box model

Model dynamics

- Steady-state models
- Linear dynamic models
- Nonlinear dynamic models

The features used by the fault detection classifier from a model-based preprocessor could be the differences between measured and modeled performance (i.e., innovations), physical parameters of the model (e.g., air-side heat transfer conductance), or characteristic quantities that have some dependence on inputs (e.g., compressor efficiency). Both physical and black box models have been used for FDD. A black box model provides a mapping between inputs and outputs of a process or system, but does not take into account any known physics. Black box models can provide excellent mappings to nonlinear behavior, but require much more data for training than models based upon physical laws and may not extrapolate well. Examples of black box models include artificial neural networks, polynomials, and autoregressive (AR) models. Models that combine empirical parameters with some physics are often termed gray box models. Transients are often neglected in models used for FDD. However, the use of steady-state models requires that the FDD method have a steady-state detector to evaluate when the FDD method is applicable. State-space representations have been used to track systems whose dynamics are nearly linear. A Kalman filter provides a means of estimating unobservable states for linear systems based upon available measurements. In some cases, neither steady-state nor linear dynamic approaches are valid and nonlinear dynamic models are employed.

In a broad sense, the fault detection classifier is an expert system. The knowledge necessary to make a fault decision can be stored in a number of forms, including a set of production rules (i.e. IF, THEN, ELSE rules), a fault tree, and conditional probabilities for statistical pattern recognition classifiers. Typically, it is necessary to assign the thresholds for deviations between current and normal performance that constitute faults. In selecting thresholds, there is a tradeoff between detection sensitivities and false alarm rates. Tighter thresholds result in greater sensitivities (detection of smaller faults), but will lead to more false alarms (an indication of a fault that doesn't exist). Thresholds are often determined based upon heuristics, although better performance (lower ratio of false alarms to correct diagnoses) is achieved when statistical thresholds are employed.

In general, preprocessing simplifies the classification and improves overall performance of the FDD system. In the absence of any preprocessing, the FDD system is a classic expert system. All fault detection is then based upon rules that act directly on the measurements. For instance, a chiller application might use condenser head pressure as an indication of a fault. Without preprocessing, the head pressure would be compared with a fixed maximum value to indicate a fault. However, since the head pressure varies under normal operation with the entering condenser water (or air) temperature, the fault detection threshold must be greater than the highest head pressure associated with normal operation. A more complex expert system might contain a set of rules with different head pressure limits for different condenser water temperatures.

Alternatively, a model-based preprocessor could model the relationship between head pressure and condenser water (or air) inlet temperature under normal operation. Then, a fault would be identified if the deviations between measured and modeled head pressures exceeded a specified threshold. The FDD system with the model-based preprocessor can be significantly more sensitive to abnormal behavior than the single rule system and easier to implement than the expert system with many rules. The thresholds for allowable deviations can be established by evaluating the statistical properties of the measurements, and how well the model for normal operation fits the measurements.

<u>Fault Diagnosis</u>

The structure of Figure 1.2 can also be used to describe fault diagnosis. Measurements are processed in order to simplify the classification required to identify the particular component at fault. The overall classification problem is different for fault diagnosis than fault detection in that the decision is not binary (i.e., fault/ no fault): the classifier must choose the specific fault from a list of possibilities. However, the diagnostics problem can be reduced to a series of fault detection problems through fault isolation.

With fault isolation, fault detection methods are applied to individual components for which diagnoses are desired. For instance, condenser fouling in an air conditioner could be detected by estimating the heat exchanger effectiveness from measurements on the condenser. The fault is diagnosed as soon as it is detected and no additional classification is necessary. The disadvantage of fault isolation is the large number of measurements required. The diagnosis of heat exchanger fouling would require measurements of all states entering and leaving the heat exchanger.

Another diagnostic approach involves comparing physical parameters determined from measurements with values representative of normal operation. For instance, heat exchanger conductance could be estimated from entering and leaving conditions and used to diagnose fouling. Here again, fault detection and diagnosis are combined and no separate diagnostic classification is necessary.

A more common diagnostic approach that requires fewer measurements involves the use of fault models. For each type of fault to be diagnosed, a fault model predicts the outputs associated with the occurrence of that fault for a current set of inputs. The fault is diagnosed through the use of a classifier that attempts to find the fault model with the best representation for the current behavior. The advantage of fault modeling for diagnosis is that fewer measurements are required. However, it is necessary to have fault models for each fault and combinations of faults to be diagnosed. Statistical pattern recognition techniques are often employed for finding the best matching fault model. However, when sufficient data are available for training, neural network and other black box approaches can learn patterns for normal and faulty behavior and provide direct classification of raw measurements.

<u>Fault Evaluation</u>

Fault evaluation follows fault detection and diagnosis and requires an evaluation of the impact of a fault on system performance. Without this step, the fault must become obvious enough to justify the expense of servicing the unit. This is the case for many “hard” failures, such as broken fan belts or seized compressors. However, fault evaluation is necessary for many performance degradations, such as heat exchanger fouling, where the fault could be detected and diagnosed well before the need for service.

1.4.4 FDD Methods for Vapor Compression Cooling Equipment

The application of FDD techniques to cooling equipment has only begun within the past few years. This application is very different than the earlier applications because it will not tolerate high initial costs (i.e., the processes are not critical and do not involve production). However, FDD has become increasingly attractive for HVAC as the cost of micro-processors and other electronics has gone down and as service organizations are growing and looking for ways to reduce labor costs. Recently, a number of researchers from around the world collaborated to investigate FDD methods for HVAC&R equipment through an International Energy (IEA) collaborative effort (Hyvärinen and Kärki, 1996).

The available literature relating to fault detection and diagnosis (FDD) applied to vapor compression cooling equipment is very limited. Most of the work has focused on the fault detection and diagnostic steps. This includes contributions from McKellar (1987), Stallard (1989), Yoshimura and Ito (1989), Kumamaru et al. (1991), Wagner and Shoureshi (1992), Inatsu et al. (1992), Grimmelius et al. (1995), Gordon and Ng (1995), Stylianou and Nikanpour (1996), Peitsman and Bakker (1996), Stylianou (1997), Rossi and Braun (1997), and Bailey (1998). For the most part, the methods developed involve the use of thermodynamic measurements to detect and diagnosis common faults that degrade system cooling capacity and efficiency and impact the life of equipment. The use of temperature measurements is appealing because of the relatively low cost requirements for this application. The faults considered include compressor valve leakage, heat exchanger fan failures, evaporator frosting, condenser fouling, evaporator air filter fouling, liquid line restriction, and refrigerant leakage. Of these studies, only Grimmelius et al. (1995), Stylianou (1997), and Bailey (1998) developed FDD methods for chillers.

McKellar (1987) identified many of the common faults for home refrigerators and investigated the effects of several faults on thermodynamic measurements within the vapor compression cycle. The faults that he considered were compressor valve leakage, heat exchanger fan failures, frost on the evaporator, partially blocked capillary tube, and refrigerant charging failures. McKellar found that each of these faults had unique effects on three measures: suction pressure (or temperature), discharge pressure (or temperature), and discharge-to-suction pressure ratio and concluded that these measures were sufficient for developing a FDD system. He did not develop a general approach to characterizing expectations for these measurements (i.e., a model-based preprocessor) nor did he discuss thresholds for fault detection and diagnostic classifiers.

Based upon the work of McKellar, Stallard (1989) developed an expert system for automated FDD applied to refrigerators. Condensing temperature, evaporating temperature, condenser inlet temperature, and the ratio of discharge-to-suction pressure were used directly as classification features (i.e., no model-based preprocessor). Feature limit checking, the simplest of rule-based classifiers, was used for both detection and diagnostic classification. Fault diagnoses were performed by evaluating the direction in which classification features changed from expected values and then by matching these changes to expected directional changes associated with each fault (when they exceeded the fixed threshold). Different rules were used for each of three discrete ranges of ambient temperature.

Wagner and Shoureshi (1992) used a different approach to perform FDD for refrigerator faults. Dynamic, nonlinear state estimation techniques were used to generate residuals between current and expected states. Compressor shell temperature, condensing temperature, and compressor power were measured system responses, and ambient temperature was a measured model input. Experiments were used to develop dynamic fault models for each of the faults considered. On-line measurements were statistically compared with normal and fault models in order to perform diagnostic classification.

Kumamaru et al. (1991) used characteristic curves to obtain quantitative expectations for heat pump performance as a function of cooling water temperature and loading. Diagnostics were performed using residuals as input features. The method did not utilize statistically based thresholds and did not detect performance degradations.

Yoshimura and Ito (1989) used a combination of seven temperature and pressure measurements to perform FDD for packaged air conditioners. Their method used rules with fixed thresholds to perform detection and diagnosis. They did not utilize any preprocessing or statistical rule evaluation.

Inatsu et al. (1992) developed a refrigerant leak detection method for automotive air conditioners that used a measurement of the liquid to gas flow ratio in the liquid line. The method did not utilize any model-based preprocessing to account for the effects of ambient temperature and load conditions on expectations for this measurement and utilized fixed thresholds. As a result, the method could only detect refrigerant loss with a sensitivity of about 60% of full charge.

Grimmelius et al. (1995) used differences between measurements and outputs of steady-state models for expected behavior as input features for detection and diagnosis of chiller faults. The method used approximately 20 measurements, including temperatures, pressures, power consumption, and compressor oil level. Diagnoses were performed using a pattern recognition technique applied to the current residuals and a matrix of expected residual changes associated with each possible fault. The fault matrix was determined using experiments on a chilled water system to which faults had been introduced.

Gordon and Ng (1995) developed a thermodynamic model for COP and capacity of chillers that could be used to generate characteristic quantities for use within a fault detection method. Stylianou and Nikanpour (1996) and Stylianou (1996) used this model as part of their FDD approach applied to a reciprocating chiller. This model was used solely for fault detection (not diagnosis) during steady-state operation of the chiller. Diagnostics were performed in a manner similar to that presented by Grimmelius et al. (1995). Stylianou (1997) added a statistical evaluation of the model residuals in order to improve the diagnostic classifier. Very limited evaluation of the FDD method was presented.

Rossi and Braun (1997) presented an FDD method for packaged air conditioners using nine temperature measurements and one humidity measurement to detect and diagnose five faults: refrigerant leakage, liquid line restriction, leaky compressor valves, fouled condenser coil, and dirty evaporator filter. The FDD technique uses a steady-state model to predict temperatures in a normally operating unit in order to generate innovations or residuals for both the fault detection and diagnostic classifiers. The magnitudes of the residuals are statistically evaluated to perform fault detection and compared with a set of rules based on directional changes to perform fault diagnosis.

Rossi and Braun (1997) only performed limited evaluations of their method for a rooftop air conditioner. More recently, Breuker and Braun (1998b) did extensive experimental evaluations of the performance of this FDD technique. Steady state and transient tests were performed on a simple rooftop air conditioner in a laboratory over a range of conditions and fault levels. The data without faults were used to train the models for normal operation and determine statistical thresholds for fault detection, while the transient data with faults were used to evaluate FDD performance. The effect of a number of the design variables on FDD sensitivity for different faults was evaluated and two prototype systems were specified for more complete evaluation. Good performance was achieved in detecting and diagnosing five faults using a "low-cost" design with only six temperatures (2 input and 4 output) and linear models. Refrigerant leakage, condenser fouling, and liquid line restriction were detected and diagnosed before an 8% reduction in capacity or COP occurred. The technique was less sensitive to evaporator fouling and compressor valve leakage, but was still able to detect and diagnose them before a 12% and almost 20% reduction in capacity and COP respectively. On average, the performance improved by about a factor of two when ten measurements (three input and seven output) and higher order models were utilized.

Peitsman and Bakker (1996) used black box models to generate residuals for a FDD method that was applied to a laboratory chiller. Models were used at the system level for fault detection and at the component level to isolate the fault (fault isolation approach). Both ARX and neural network models were investigated. Only limited evaluation of the FDD method was presented.

Bailey (1998) trained an artificial neural network (NN) using normal and fault data from a screw chiller in order to provide direct classification of normal and faulty performance. The data were collected during transient operation with the chiller meeting a time-varying load under variable ambient conditions. The NN model used a large number of inputs to predict the output classes and therefore required a very large data set. It's not clear from the results, whether the method performs well in extrapolating beyond the data set used for training.

Rossi and Braun (1996) appear to be the only researchers to address the fault evaluation step of Isermann's process supervision for air conditioning equipment. They defined four criteria in evaluating the need for service: comfort, safety, environment, and economic. In general, service should be performed whenever: 1) comfort cannot be maintained, 2) equipment or personal safety is compromised, 3) environmental damage is occurring (e.g., refrigerant leakage), or 4) reduced energy costs justify the service expense. They presented results associated with maintenance scheduling for heat exchangers that were determined using the fault evaluation criteria described above. A simplified method for estimating the optimal service times that minimize combined energy and service costs for cleaning condensers and replacing evaporator filters in air conditioners was developed and evaluated.

1.5 Needs for Future Work

There are several opportunities for future work related to FDD for chillers. Clearly, there is a need to identify the most important faults for chillers. This could be accomplished using a study similar to the one performed by Breuker and Braun (1998a) for rooftop air conditioners where frequency of occurrence and relative costs were estimated for a variety of fault categories. Ideally, it would be best to have a database from a variety of manufacturers and to perform separate analyses for different chiller types. The results of ASHRAE 1043-RP may not satisfy these goals.

Although a variety of FDD methods have been proposed for chillers and other vapor compression equipment, very little evaluation of the methods has been performed. The first step in this process is to develop a detailed set of data for normal and faulty behavior that can be used to determine the sensitivity of FDD methods in correctly diagnosing faults. ASHRAE 1043-RP should provide measurements and modeling tools useful for this purpose. Once data exists, it would be useful to explore the performance of a variety of FDD methods. The NIST test shell could be an appropriate platform for evaluating alternative methods developed by different researchers. Ultimately, this work would lead to the development of a toolbox of techniques that could be used in a general design and evaluation environment for FDD systems. In the course of this work, it would be necessary to develop indices for comparing different FDD techniques and guidelines for their application to vapor compression equipment.

Several criteria would be important in comparing different FDD approaches, including: 1) sensor requirements, 2) training requirements, 3) computational effort, and 4) sensitivity in correctly diagnosing faults. There is a need for some standard indices and methods for comparing the performance of the different FDD methods. Standard data sets are certainly one important step in the process.

1.6 Additional References

The following papers fall within the scope of this report, but were not reviewed either due to the general nature of the papers or the lack of fresh information. Moreover, special attention should be given the books by Chen (1999), Gertler (1998), and Mangoubi (1998), which provide general tools to solving FDD problems and have only recently been made available.

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2.0 FDD Methods

2.1 Chiller Applications

2.1.1 The Design and Viability of a Probabilistic Fault Detection and Diagnosis Method for Vapor Compression Cycle Equipment

Author: Margaret Bailey

Overview

A Neural Network (NN) fault detection and diagnostic program was trained using chiller operating data collected during both normal and abnormal operating conditions. The faults introduced included refrigerant loss and overcharge, oil loss and overcharge, air-cooled condenser fouling, and the loss of an air-cooled condenser fan (chosen as a result of surveys conducted with a chiller manufacturer and chiller service contractor).

FDD Method

NNs are particularly suited for modeling highly non-linear processes and are also known for their ability to ignore excess data that is of minimal importance and concentrate on more crucial input data.

Type T thermocouples were used for most temperature measurements, an RTD measured the chilled water temperature, and thermistors measured refrigerant condensing and evaporating temperatures. Sensor data included: superheat for circuits 1 and 2 (each circuit had its own compressor), subcooling for circuits 1 and 2, power consumption, suction pressure for circuits 1 and 2, discharge pressure for circuits 1 and 2, chilled water inlet and outlet temperatures from the evaporator, and chiller capacity.

Two independent variables, fault degree and chiller load, were varied to study the following dependent variables: energy consumption, chilled water supply temperature, superheat and subcooling temperatures, suction pressure and discharge pressure. Another approach considered the effects of outdoor air temperature (an uncontrollable independent variable) and chiller load on the same dependent variables.

A table of relationships between outdoor air temperature, percent refrigerant charge, and percent nominal chiller load on the dependent variables are listed on page 109 of Bailey (1998).

A multiple linear regression model and a non-linear neural network model were used to verify that all the independent variables were important in determining the dependent variables.

The inputs to the NN classifier included: time step, outdoor air temperature, chilled water setpoint, evaporator approach temperature, evaporator entering water temperature, evaporator leaving water temperature, superheat temperature, condenser approach temperature, saturated evaporator temperature, condensing temperature, apparent power, oil entering temperature, compressor suction temperature, the EXV position, and several others.

Two classifier designs were studied to evaluate their performance; these classifiers were the non-parametric K-Nearest Neighbors (KNN) and Mean Square Error (MSE) criterion. Depending on how the samples were divided, the average misclassification rates of the KNN and MSE classifiers ranged from 25% to 36% with no significant difference between them. Therefore, the linear and non-parametric classifiers proved to be inadequate for chiller detection and diagnostics. These two classifiers were tested to determine which factors significantly affected classifier performance. It was found that using transient data resulted in poor performance. Moreover, the way in which data were collected in different time segments was also critical.

The multi-layered perceptron (MLP) neural network class was used as the basis for the chiller FDD method. Although the MLP is generally more difficult to set up than the radial basis function (RBF), it can screen out irrelevant inputs better than the RBF.

Chiller data consisted of 51 features collected at 6-second intervals over a 2-month period in the summer of 1996. The training, validation, and testing data sets were all independent from each other during each day's testing. The three data groups were selected according to natural time steps where chiller operation underwent a change in operation. The training data set was largely made up of the first three hours of chiller operation (start-up and first two-thirds of chiller loading). The validation data included the final one-third of the chiller loading and part of the steady state operation. The testing data set was composed of the final steady state operating period. Input data were preprocessed by subtracting the mean, and then dividing by the standard deviation. The NN was trained by adjusting weights and biases to minimize an error function. The training pattern included the input data and the corresponding target data, which is known as supervised training. After training the NN, additional input data with known outputs was used to test the accuracy of the NN. All the corresponding training, validation, and testing files were used at each step in the analysis (with a few exceptions).

FDD Evaluation

Laboratory tests were done using a Trane 70-ton RTUA Air-Cooled Chiller (screw compressor using HCFC-22) coupled with a Trane 50-ton CAUA Air-Cooled Refrigerant Condenser. The unit provides chilled water to an air-handling unit used for environmentally controlled rooms (zones); therefore, a simulated load can be imposed on the chiller. The chilled water contained 25% by weight ethylene glycol. The air-cooled condenser has six constant-speed fans; operation of the fans is staged based on compressor discharge pressure. The chiller has two compressors—if the load is small enough, only one compressor is used. Furthermore, each compressor is on a different circuit. When conducting fault tests, circuit 2 was typically left in a nominal operating condition while circuit 1 was operated in the fault condition.

The chiller load was increased from 0 to 65 tons during the course of each day's testing to simulate outdoor conditions ranging from 55°F to 100°F. The outdoor temperature was not controlled; it varied naturally throughout the course of each day.

Refrigerant charge in circuit 1 was started at -60% and increased each day by +5% until +30% overcharge was reached. Circuit 2 had -20% refrigerant charge the first day and then was kept at the recommended level for the remainder of the testing.

Oil charge was started at -50% in circuit 1 and each day some oil was added until at the end of 5 days there was a +35% overcharge. Circuit 2 was kept at the recommended level.

Air-cooled condenser fouling was simulated by covering the air intake screens. The fouled surface area on circuit 1 started at 22% and was increased to 67% over 5 days. Circuit 2 was kept open except for one test where circuits 1 and 2 were both fouled at 37%.

Air-cooled condenser fan loss was simulated on circuit 1 by individually turning off first fan 1 (affecting stages #1 and #3), then fan 2 (affecting stages #2 and #3). Fans on circuit 2 remained on.

FDD Results

The NN classifier outputs were:

1. Normal operation
2. Refrigerant loss
3. Refrigerant overcharge
4. Oil loss
5. Oil overcharge
6. Condenser fan loss
7. Condenser fouling

Section 5.4.5 of Bailey (1998) states that the misclassification rate of the NN (using an unknown training file) was 9% overall when tested using the test data. The misclassification for outputs 1, 2, 3, 6, and 7 were less than 0.1%. The misclassification rate for output 4 was 7.9% and it was 1.0% for output 5. These results are listed as a sample output; therefore, it cannot be ascertained whether these are truly valid results.

In section 5.4.6 a further study was performed to check the accuracy of the NN via a parametric study (it is not clear how the results of this study compare with the sample output in section 5.4.5). 19 different training programs were used, and among these the best true performance was training file 12 with a 0% misclassification rate of the training data, a 3% misclassification rate of the validation data, and a 20% misclassification rate of the test data. However, this particular training set achieved superior results by not using any fan loss data. Training file 18 achieved better success with a 0% misclassification rate of the training data, a 1% misclassification rate of the validation data, and a 9% misclassification rate of the test data. Unfortunately, the training data included fault degree information, thus making the results invalid.

Bailey, M.B., 1998, "The Design and Viability of a Probabilistic Fault Detection and Diagnosis Method for Vapor Compression Cycle Equipment," Ph.D. Thesis, School of Civil Engineering, University of Colorado.

2.1.2 On-line Failure Diagnosis for Compression Refrigeration Plants

Authors: H. T. Grimmelius, J. Klein Woud, and G. Been

Overview

A prototype condition monitoring and diagnostic system was developed in response to the need for evaluating faults in compression refrigeration plants. Earlier work was focused on condition monitoring of ship machinery, including the compression refrigeration plant. Using expert knowledge and simulated failure data, a failure mode symptom matrix was developed. Fuzzy logic was used to recognize these faults.

FDD Method

A reference system is placed in parallel to the actual system. The outputs from the two are compared in a diagnostic module based on the following criteria:

1. Description of possible failure modes
2. Symptom patterns of these failure modes
3. Reference values for monitored variables, in healthy system condition, given the actual environmental and loading conditions
4. Effective diagnostic strategy

A feasibility study was carried out in which a failure mode and effect analysis (FMEA) was done. The results were combined with expert knowledge obtained from interviews with system and component designers and service engineers.

The cooling plant was divided into the following 7 components for the FMEA study:

1. Compressor, including suction and discharge lines and valves
2. Condenser
3. Liquid line, including filter drier
4. Liquid line with solenoid and sight glass
5. Thermostatic expansion valve with external pressure compensation
6. Evaporator
7. Crankcase heater

Only steady state symptoms were studied, leading to 58 possible failure modes. Measurement variables were chosen to indicate when a particular symptom was present. The cause-effect procedure started with a selection of serviceable parts, moved to possible failure modes, then looked at their influence on the component, their influence on the system, and concluded with the measurable variables.

Some of the measured variables were: suction pressure, crankcase pressure, oil pressure, discharge pressure, pressure after evaporator, pressure drop across filter, refrigerant suction temperature, refrigerant discharge temperature, refrigerant temperature after condenser, refrigerant temperature before/after evaporator, cooling water temperature before/after condenser, cooling water temperature before/after evaporator, ambient temperature, and electrical current into compressors one and two.

In developing the symptom matrix, those failure modes with identical patterns were combined and those with empty patterns were divided into two groups: ones with no measurable effects and ones that affect only transient behavior. The symptom matrix was thus reduced to 37 failure modes.

The paper appears to state that refrigerant leakage has no measurable effects based on the variables used in this study. Instead, the authors recommend using special detection sensors.

The diagnostic model performs some preprocessing of the data that includes checks for sensor faults. It also uses a geometric moving average to smooth out temporary disruptions. Finally it neglects data recorded during transient behavior caused by a change in the number of cylinders operating.

In the symptom matrix a score is assigned to each variable to indicate the relative weight of that measurement to the fault being described. The score was assigned based on expert knowledge. All the scores of matching patterns are added together and divided by the total possible score for a given fault. A score greater than 0.9 is indicated as a probable fault, a score between 0.5 and 0.9 is a possible fault, and a score below 0.5 is not likely a fault.

The data acquisition, presentation, and diagnostics modules are all independent. A failure in one module can be detected and reported by another module without a complete system breakdown.

FDD Evaluation

The compression refrigeration plant used three 6-cylinder compressors, a water-cooled condenser, and a water-chilling evaporator. The capacity was about 77 tons (3.516 kW equals a ton) at a chilled water temperature of 6.5-12°C (44-54°F) and a cooling water temperature of 20-35°C (68-95°F). The refrigerant used in the chiller was R22. Only the first two compressors were used during measurements.

The water flow rates remained constant throughout the testing period. The chilled water inlet temperature was varied from 4 to 14°C (39-57°F). The cooling water inlet temperature was varied from 24 to 32°C (75-90°F).

A reference value estimator was calculated using linear regression with a maximum of nine coefficients.

It is not clear whether all 37 failure modes were tested. Results were presented only for the 5 modes listed in Table 2.1.

Table 2.1 Selected failure modes of chiller

	Failure Mode	Simulation Method
1a	Compressor, suction side, increased flow resistance	Throttling compressor suction valves
1b	Compressor, discharge side, increased flow resistance	Throttling compressor discharge valves
2	Condenser, cooling water side, increased flow resistance	Reducing cooling water flow
3	Fluid line, increased flow resistance	Throttling fluid line valve between condenser and filter
4	Expansion valve, control unit, bulb loosened from pipe	Increasing thermal resistance by adding isolation between bulb and pipe
5	Evaporator, chilled water side, increased flow resistance	Reducing chilled water flow

FDD Results

The residuals of the suction pressure were shown in several plots. The vast majority of the suction pressure readings were shown to be in the range of 4 to 5 bars, with the residuals generally lying within ±0.15 bars.

The residuals of the cooling water outlet temperature were also shown in several plots. The measured values were in the range of 30-40°C (86-104°F) and most of the residuals were within ±1°C.

The R^2 fit exceeded 0.94 for all the variables except oil temperature and one pertaining to the number of active cylinders.

All faults were introduced at levels below that which would cause an alarm condition. The results from the introduction of fault 5 were presented on graphs of the suction pressure and cooling water temperature against time and indicated when the fault was introduced and removed. For fault 5, the suction pressure dropped noticeably outside of its predicted range, but the cooling water temperature just barely dropped below the expected range. Based on the measurements made, some revision was done to the symptom matrix created by the FMEA.

The system's drawback may be that it concludes too early that a particular fault has occurred without many symptoms being found. It also requires a new regression analysis for each installation. And it cannot detect faults during transient behavior.

The reference values were accurate enough to determine a fault at an early stage of development.

Grimmelius, H.T., J.K. Woud, and G. Been, 1995, "On-line Failure Diagnosis for Compression Refrigeration Plants," *International Journal of Refrigeration*, Vol. 18, No. 1, pp. 31-41.

2.1.3 Application of Black-Box Models to HVAC Systems for Fault Detection

Authors: Henk C. Peitsman and Vincent E. Bakker

Overview

Two types of black-box models—multiple-input/single-output (MISO) ARX models and artificial neural network (ANN) models—were applied for fault detection and diagnosis (FDD) in an HVAC system. Two levels of models were established, the system models and component models. System models detected faulty behavior of a system, while component models located the defective component. For nonlinear systems, it was found that ANN models fit better than ARX models.

FDD Method

A single-input/single-output (SISO) autoregressive with exogenous inputs (ARX) model can be represented in its simplest (linear) form by:

$$y(t)+a_1y(t-1)+\cdots+a_{na}y(t-na)=b_1u(t-1)+\cdots b_{nb}u(t-nb)+e(t)$$

where y is the output, u is the input, t is time, t-n is the time n steps previously, e is the model error, and a and b are the coefficients of the model.

To achieve an improved ARX model for nonlinear systems, several approaches are proposed. One is to add extra inputs (physical inputs and artificial inputs). Another possibility is to use predicted historical outputs as new model inputs. The performance of the model can also be improved by subtracting the mean values from the input and output signals.

Each process output variable has its own ARX model.

The ANN model is usually built up of three layers: the input layer, the hidden layer, and the output layer. The three layers are connected in a nonlinear way. In this study, the back propagation algorithm was used to train multi-layered feed-forward networks with a log-sigmoid transfer function.

Measured observation data from the previous time step and the predicted values for the output from the two previous time steps were used as model inputs. The network predicts all system model outputs.

A data set that meets the following two conditions can be used to train the ARX models and the ANN model:

- A healthy and dynamic data set that is measured under optimal or good operation conditions of the system over a large working range
- The availability of a data set with a fixed time step.

To detect faulty operation, the predicted outputs of the model are compared to the measured output of the system. If the value of the measured output is not within the bounds of the predicted output, it suggests that there is an error in the system or an incorrect model was used.

Several indexes are used in the model evaluation:

1. Reliability coefficient (r^2) is:

$$r^2 = 1 - \frac{\sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}$$

   where $y_{i,}$ [redacted], $\bar{y}$ are the measured, estimated and average output values of Y, respectively. The reliability coefficient has a value between 0 and 1, where a value of 1 means the model fits the measured output perfectly.
2. The auto-correction coefficient, a measure of the closeness of the relationship between a time series and the same time series one time step back.
3. Standard deviation and average error of residuals.
4. The cross validation error, which is defined as the sum-square error of residual of the test data.

FDD Evaluation

The process was applied to a laboratory chiller and a simulated variable-air-volume (VAV) system. For the fault detection of the chiller, observation data were collected from a data logger every 10 seconds. The sensor readings that were used as inputs for the ARX and ANN system models were: condenser supply water temperature, evaporator supply glycol temperature, instantaneous compressor power, and the flow rate of cooling water entering the condenser (ANN only). These magnitudes were selected because of their universal availability in building automation systems. By combining the three physical inputs, the total number of inputs to the ARX model for the whole system was artificially increased to nine.

Models for the refrigerant components (e.g., condenser, expansion valve, evaporator, compressor, and subcooler) were established. The structures of the ARX and ANN inputs of the component models were the same as those described for the system models. For each component, different network models were used because each component had different physical inputs.

The VAV application was based on ARX models. The total number of inputs used for deriving the system model of the AHU included six measured inputs, eighteen derived inputs, and historical inputs—which are the values of the 24 inputs from the four previous time steps. Two outputs—the outlet air temperature after the supply fan and supply air mass flow rate—were predicted.

Models for the VAV components (e.g., the mixing box, cooling coil, heating coil, supply fan and return fan) were established. The paper presented the structure of the cooling coil model in detail.

FDD Results

The chiller model results showed that the reliability of the ARX and ANN models was approximately 97% for normal operation. Fault detection using discharge refrigerant pressure when air was in the system was demonstrated. The author did not mention how the fault was simulated or to what severity.

Comparison of neural networks with ARX models showed that ANNs give slightly better results for the system model and component models than ARX models.

The author emphasized the importance of the choice of initial state for the training of ANNs. "It is crucial to find the global minimum of the residue, that is, the smallest sum of squared errors."

ARX model results for the AHU showed that it was capable of detecting a known fault. The actual fault was not mentioned; however, the possibilities can be traced to one of three causes within the cooling coil system.

Peitsman, H. and V. Bakker, 1996, "Application of Black-Box Models to HVAC Systems for Fault Detection," *ASHRAE Transactions*, Vol. 102, Pt. 1, pp. 628-640.

2.1.4 Performance Monitoring, Fault Detection, and Diagnosis of Reciprocating Chillers

Authors: Meli Stylianou and Darius Nikanpour

Overview

This paper presents a system for detecting and diagnosing faults for a reciprocating chiller. The system is composed of three modules for detecting faults: one used with the chiller off, one used during start-up, and one used at steady-state conditions.

FDD Method

The following variables were measured: discharge temperature, high pressure liquid line temperature, high pressure liquid line temperature before filter dryer, low pressure liquid line temperature, suction line temperature, crankcase oil temperature, evaporator entering water temperature, evaporator leaving water temperature, condenser entering water temperature, condenser leaving water temperature, crankcase oil pressure, discharge pressure, suction pressure, high pressure liquid line pressure after filter dryer, condenser water flow rate, and evaporator water flow rate.

The off-cycle module is active as soon as the chiller is turned off. It is used primarily to check sensor reliability (the goal is to use software to reduce reliance on sensor redundancy). The operator is alerted to any detected faults before the next start-up.

The start-up module is active for about the first 15 minutes of chiller operation. It is used to detect refrigerant flow faults, since they are easier to find before the system reaches steady state. It uses only four variables as inputs: the discharge temperature, the crankcase oil temperature, and the refrigerant temperature entering and leaving the evaporator. The transient response period makes the diagnosing of certain faults independent of the TXV's influence.

For the start-up module the following faults may be detected through the collected sensor data:

- A shift (in time and or magnitude) in the peak of the discharge temperature may indicate liquid refrigerant floodback, refrigerant loss, or refrigerant line restriction
- A shift in the inflection of the refrigerant temperature entering the evaporator may indicate refrigerant line restriction or refrigerant loss
- A shift in the slope or minimum of the crankcase oil temperature may indicate liquid refrigerant floodback or thermal expansion valve fault
- A shift in the change of refrigerant temperature through the evaporator may indicate refrigerant leak or restriction in refrigerant line

The physical and thermodynamic causes for detecting faults in the start-up module are not explained. Furthermore, only the changes in the discharge temperature and suction line temperature were presented. One possible explanation for the peak in the discharge temperature is that the TXV begins to open at that point and thereby causes the reduction in the discharge pressure and temperature. Moreover, with a refrigerant leak or flow restriction, an opening TXV has minimal impact since it doesn't initially constrict much flow. Consequently, the discharge pressure doesn't decrease and the temperature no longer exhibits a peak.

The steady-state module is active once the chiller reaches steady state. It checks to make sure the chiller is operating within acceptable energy performance limits and is used to detect faults which cannot be compensated for by the TXV.

The steady-state module checks the chiller's performance against optimal levels and also seeks to detect and classify predetermined faults. The thermodynamic model to determine actual chiller performance was obtained from Gordon and Ng (1994). The steady-state model requires training data collected after installation in order to be effective.

The fault pattern used in the steady-state diagnostic model is listed in Table 2.2.

Table 2.2 Fault pattern of diagnostic module

Fault	Discharge temp	High pressure liquid line temp	Discharge pressure	Low pressure liquid line temp	Suction line temp	Suction pressure	ΔTcond	ΔTevap
Restriction in refrigerant line	+	-	-	-	+	-	-	+
Refrigerant leak	+	-	-	-	+	-	-	+
Restriction in cooling water	+	+	+	-	-	-	+	-
Restriction in chilled water	+	-	-	-	-	-	-	-

The '+' signifies an increase in the measured variable, and a '-' corresponds to a decrease. Evaporator and condenser water entering temperatures are used as independent variables.

FDD Evaluation

Normal operating conditions were mapped by changing the setpoints of the entering water temperatures of the condenser from 22°C to 34°C (71.6°F to 93.2°F) and the evaporator from 10°C to 15°C (50°F to 59°F). All RTDs except for the one measuring the crankcase oil temperature were dry surface-mounted. Data were collected every 10 seconds.

The faults were simulated in laboratory tests on a 5-ton commercial reciprocating chiller using R-22.

- Refrigerant leak simulated by removing refrigerant
- Refrigerant line restriction simulated by throttling after condenser (represents plugged filter-drier, etc.)
- Condenser water flow restriction simulated by reducing water flow (represents fouling, pump fault, etc.)
- Evaporator water flow restriction simulated by reducing water flow (represents fouling, pump fault, etc.)

Refrigerant floodback at start-up was another fault used to test the FDD system; however, it was not deliberately introduced since it naturally occurred in the tested chiller due to an undersized evaporator.

FDD Results

A flow restriction at 85kPa and 140kPa was introduced in the refrigerant line. The TXV reacted to the flow restriction by opening in order to maintain the desired superheat, which limited the sensitivity of the rule-based pattern recognition approach.

For the start-up module, both a refrigerant line obstruction and loss of refrigerant charge were tested. The collected data verified a fault was present, but currently no work has been done to classify faults based on this data.

No sensitivity or false alarm information is presented for the steady-state FDD module.

More work needs to be done to determine whether the start-up module as tested on the laboratory unit is applicable to all reciprocating chillers.

Stylianou, M. and D. Nikanpour, 1996, "Performance Monitoring, Fault Detection, and Diagnosis of Reciprocating Chillers," *ASHRAE Transactions*, Vol. 102, Pt. 1, pp. 615-627.

2.1.5 Application of Classification Functions to Chiller Fault Detection and Diagnosis

Author: Meli Stylianou

Overview

A prior study by Stylianou and Scott (1993) identified the most common faults occurring in commercial vapor-compression units. Faults were categorized based on frequency of occurrence, cost of servicing, energy consumption, and occupant comfort. The most important faults identified in this previous report were used as the basis for those studied in the current paper.

The report focuses on using a statistical pattern recognition algorithm (SPRA) for fault detection and diagnosis of commercial reciprocating chillers.

FDD Method

The method is an extension of the one presented by Stylianou and Nikanpour (1996). The difference is that a statistical pattern recognition approach SPRA is substituted in place of the rule-based steady-state method used in the earlier paper.

The SPRA uses chiller models to predict temperatures and pressures at different points in the refrigeration circuit. The models are a set of bilinear equations. Evaporator and condenser water entering temperatures were used as inputs in conjunction with the following dependent variables: discharge temperature, high-pressure liquid-line temperature, low-pressure liquid-line temperature, suction line temperature, evaporator leaving water temperature, condenser leaving water temperature, discharge pressure, and suction pressure.

Innovations (differences between measured and predicted values) are used as inputs to the SPRA. The SPRA is based on the Bayesian decision rule, and uses statistical training data to derive a family of classification functions. Classification is made into one of the five classes—a normal class and four fault classes—in one step. The score for a particular class j is calculated by:

$$d_j(x) = \left(x - \frac{1}{2} x^{-j} \right) \hat{\sum}^{-1} x^{-j^T}$$

where x is the vector of innovations and $\hat{\sum}$ is covariance matrix of the training data for normal operation

The model's output is classified according to the class with the highest score; however, the importance of the actual value or relative magnitude is not mentioned.

FDD Evaluation

Normal operating conditions were mapped by changing the setpoints of the entering water temperatures of the condenser from 22°C to 34°C (71.6°F to 93.2°F) and the evaporator from 10°C to 15°C (50°F to 59°F).

Except in those cases where water flow was reduced to simulate a fault, all tests were run at constant water flow. No mention is made of partial load scenarios.

The faults were simulated in laboratory tests on a 5-ton commercial reciprocating chiller using R-22. The faults were:

- Refrigerant leak simulated by removing refrigerant
- Refrigerant line restriction simulated by throttling after condenser (represents plugged filter-drier, etc.)
- Condenser water flow restriction simulated by reducing water flow (represents fouling, pump fault, etc.)
- Evaporator water flow restriction simulated by reducing water flow (represents fouling, pump fault, etc.)

The paper presents four different case studies: operating the chiller at 85% refrigerant charge, introducing a gradual restriction in the refrigerant line, reducing evaporator water flow rate, and reducing condenser water flow rate.

FDD Results

The SPRA method is designed to require little computational effort. However, it also makes some unverifiable assumptions regarding the *a priori* probabilities of each of the normal and four fault operating conditions.

The assumption of *a priori* probabilities leads to an overall miscalculation rate of 4.7%. In a test with a low refrigerant charge (85%), the highest probability was assigned correctly to refrigerant leak in 88.7% of the samples. Based on the trend in the data for the introduction of a refrigerant line restriction, the model continued to assign a higher score to it as the level of the fault increased. The threshold at which a refrigerant line restriction was detected was not revealed; however, a drop of 11 psi was shown to be enough to trigger an alarm. Water flow rate reductions of 25% were shown to be sufficient for correct classification of those corresponding faults.

Future work will be done on quantifying the sensitivity of the method; no tabular data is presented on sensitivity for the various faults.

Stylianou, M. P., 1997, "Application of Classification Functions to Chiller Fault Detection and Diagnosis," *ASHRAE Transactions*, Vol. 103, Pt. 1, pp. 645-656.

2.1.6 Chiller Condition Monitoring Using Topological Case-Based Modeling

Authors: Hiroaki Tsutsui and Kazuyuki Kamimura

Overview

Topological case-based modeling (TCBM) is a tool that can be used to model chiller performance for the purpose of monitoring. The paper compares the accuracy of TCBM with a conventional linear multiple regression model for an absorption chiller.

FDD Method

TCBM defines a system of neighborhoods in the input space that in turn map neighborhoods in the output space using continuous mapping. Each neighborhood in the output data corresponds to a neighborhood in the input data. Input variables are selected to guarantee local linearity of globally nonlinear behavior. A weighted integration technique using the outputs of similar input cases is employed when encountering new input cases. Historical data is treated as a compressed case base and estimates the output associated with new input cases according to certain case-based reasoning procedures (after an answer to a new problem is found, it is added to the case base).

TCBM differs from other black-box modeling techniques by:

1. Using continuous mapping, thus if the neighborhood map is zoomed in too much there is a loss in accuracy from the inferred output
2. Regulating only input/output variables without formalizing the relationships
3. Storing data as cases (historical data is not converted to model parameters)
4. Identifying the cases that are used in inferring new outputs
5. Estimating outputs locally by extracted cases using the neighborhood system

In the chiller model, the COP was used as the output. Five inputs were chosen: temperature of entering cooling water, temperature of leaving cooling water, chilled-water exit temperature, chilled-water return temperature, and steam flow rate (linearly related to steam temperature).

FDD Evaluation

Data were collected from an absorption chiller in the field. All data outside of 3 standard deviations of the average were eliminated to account for temporary sensor or system failures. The data were smoothed and averaged since the actual test was performance monitoring. Had fault detection been the goal, the data would not have been averaged over 24-hour periods. The data used for the model were collected over a 10-month period, followed by a 12-month period of data collected for performance monitoring.

FDD Results

An actual FDD method was not employed except the performance monitoring of the chiller. During the training phase, the TCBM model had a mean error of 0.35%, compared to 0.84% for the linear multiple regression model. When the models were used to predict COP using the test data, the linear model had a mean difference of 2.24% (2.5 times the precision of the model), whereas the TCBM had a mean difference at 7.38% (20 times the precision of the model). The TCBM model clearly showed a 10% increase in chiller performance when maintenance was performed. The same model also indicated a general decrease in chiller performance as time elapsed.

Tsutsui, H. and K. Kamimura, 1996, "Chiller Condition Monitoring Using Topological Case-Based Modeling," *ASHRAE Transactions*, Vol. 102, Pt. 1, pp. 641-648.

2.2 Packaged Air-Conditioning Equipment Applications

2.2.1 Evaluating the Performance of a Fault Detection and Diagnostic Method for Vapor Compression Equipment

Authors: Mark S. Breuker and James E. Braun

Overview

This paper presents a detailed evaluation of the performance of a statistical, rule-based Fault Detection and Diagnostic (FDD) technique presented by Rossi and Braun (1997). The FDD method for packaged air conditioners only requires nine temperature measurements and one humidity measurement to detect and diagnose five faults: condenser fouling, evaporator fouling, liquid-line restriction, compressor valve leakage, and refrigerant leakage.

FDD Method

The FDD technique uses a model to predict the expected values for temperatures in a normally operating unit as a function of the driving conditions. The expected temperatures are compared with current operating temperatures to generate residuals. The magnitudes of the residuals are statistically evaluated to perform fault detection and compared with a set of rules based on directional changes to perform fault diagnosis.

The following measurements were taken in order to characterize the fault impacts:

1. T_{amb} is the temperature of the ambient air into the condenser coil
2. T_{ra} is the temperature of the return air into the evaporator coil
3. Φ_{ra} is the relative humidity of the return air into the evaporator coil
4. T_{wb} is the wet-bulb temperature of the return air into the evaporator coil
5. T_{evap} is the evaporating temperature
6. T_{sh} is the suction line superheat
7. T_{cond} is the condensing temperature
8. T_{sc} is the liquid line subcooling
9. T_{hg} is the hot gas line or compressor outlet temperature
10. ΔT_{ca} is the air temperature rise across the condenser
11. ΔT_{ea} is the air temperature rise across the evaporator

FDD Evaluation

Both steady state and transient tests were performed in environmental chambers that can simulate indoor and outdoor conditions. The steady state data without faults were used to train models that predict outputs for normal operation. The transient data with faults were used to evaluate FDD performance.

After the FDD design was established, transient data with faults were fed to the steady state model/comparator where residuals and their associated uncertainties were estimated for all data points. The FDD detection, diagnostic and steady state classifiers used the design parameters, residuals, and residual uncertainties in order to determine no-fault and specific fault diagnoses for all of the data points. Using this approach, the performance of the FDD method was quantified across a variety of conditions and design parameters were adjusted to maximize the FDD sensitivity.

A total of 40 indoor steady state tests (each at unique temperature and humidity conditions) were included in the test data and 94 tests were considered in the training data set. The uncertainty in the steady state test results was estimated by repeating measurements nine different times over a three-week period at a single test condition.

The transients due to on/off cycling were considered at four distinct load/ambient conditions. At each building load level, faults were introduced into the test unit at four or five distinct levels (see the companion paper by Breuker and Braun, 1998a).

The set of residuals for the no-fault transient data were processed through the FDD method to determine the maximum possible fault detection threshold that yielded no false alarms for normal operation.

Two types of models, a polynomial model and a linear look-up table, were compared. The effects of polynomial order on RMS and maximum error for predicting test data were studied. Models with $T_{wb}/T_{ra}/T_{amb}$, wet/dry, T_{wb}/T_{amb}, and T_{ra}/T_{amb} as inputs were separately considered in the possibility of reducing the number of model inputs.

The impacts of steady-state detector threshold, detection error safety factor, fault probability ratio threshold and the number of output measurements on the FDD performance were evaluated.

FDD Results

The effect of increasing the order of the polynomial model showed that only the T_{sh} and T_{hg} models benefited significantly from the higher order representations. In general, linear lookup tables did not represent an improvement over the low-order polynomial models.

The three independent variable ($T_{wb}/T_{ra}/T_{amb}$) models provided the best overall FDD sensitivity of the models considered. However, the wet/dry models led to slightly better sensitivity to condenser fouling and liquid line restrictions. The T_{wb}/T_{amb} models led to good performance as compared with the three input models, whereas the performance associated with the T_{ra}/T_{amb} models was significantly worse.

Based on the effect of various design variables on FDD sensitivity, two prototypes were specified for further evaluation. The following tables demonstrate that good performance was achieved using only six temperatures (2 inputs and 4 outputs) and linear models. For each fault, the FDD method performance is quantified according to:

- the minimum level at which the fault can first be diagnosed
- the minimum level at which the fault can be diagnosed at all steady state points
- the percentage of the total operating points where the fault can be diagnosed
- the degradation in cooling capacity at the diagnosable fault level
- the degradation in COP at the diagnosable fault level

The first three faults--refrigerant leakage, condenser fouling, and liquid line restriction--were detected and diagnosed before an 8% reduction in COP occurred. Compressor valve leakage was detected and diagnosed before a 12% reduction occurred, and the least sensitive was evaporator fouling at 20%. The performance improved by about a factor of two when ten measurements (three input and seven output) and higher order models were utilized.

Table 2.3 Performance of "Low-Cost" FDD prototype

Performance Index	Refrigerant Leakage (% Leakage)		Liquid Line Restriction (% ΔP)		Compressor Valve Leak (% $\Delta\eta_v$)		Condenser Fouling (% lost area)		Evaporator Fouling (% lost flow)	
	1st	All	1st	All	1st	All	1st	All	1st	All
Fault Level (%)	9.7	12.5	9.0	10.5	17.5	20.0	16.4	19.5	27.2	Max
% Loss Capacity	5.5	7.1	4.6	5.4	10.7	12.2	3.2	3.6	15.3	>19.4
% Loss COP	3.2	4.1	3.3	3.8	11.9	13.6	4.6	6.2	13.5	>17.4
ΔT_{sh}	9.2	10.5	7.8	8.9	-5.9	-6.8	-1.9	-3.0	-4.6	<-5.5
ΔT_{hg}	7.6	9.3	7.9	9.0	0.0	0.4	2.3	2.4	-3.8	<-5.1

Table 2.4 Performance of "High-Performance" FDD prototype

Performance Index	Refrigerant Leakage (% Leakage)		Liquid Line Restriction (% ΔP)		Compressor Valve Leak (% $\Delta\eta_v$)		Condenser Fouling (% lost area)		Evaporator Fouling (% lost flow)	
	1st	All	1st	All	1st	All	1st	All	1st	All
Fault Level (%)	5.4	Max	2.1	4.1	3.6	7.0	11.2	17.4	9.7	20.3
% Loss Capacity	3.4	> 8	1.8	3.4	3.7	7.3	2.5	3.5	5.4	11.5
% Loss COP	2.8	> 4.6	1.3	2.5	3.9	7.9	3.4	5.1	4.9	10.3
ΔT_{sh}	5.4	> 11	2.3	4.8	-1.8	-3.6	-0.6	-1.6	-1.7	-2.7
ΔT_{hg}	4.8	> 10	2.4	4.8	0.0	0.0	1.8	2.3	-1.2	-2.7

Breuker, M.S. and J.E. Braun, 1998, "Evaluating the Performance of a Fault Detection and Diagnostic System for Vapor Compression Equipment," *International Journal of Heating, Ventilating, and Air Conditioning and Refrigerating Research*, Vol. 4, No. 4, pp. 401-425.

2.2.2 Development of Refrigerant Monitoring System for Automotive Air-Conditioning System

Authors: H. Inatsu, H. Matsuo, K. Fujiwara, K. Yamada, and K. Nishizawa

Overview

This paper explains a method developed to measure the amount of refrigerant in an automotive air-conditioning system. It was determined that measuring the liquid-gas flow ratio provided the best results and could identify a 40% loss of refrigerant charge under medium to high load conditions. Much of the paper was devoted to describing the liquid-gas flow ratio measurement device.

A computer simulation was created to study the system under normal and low refrigerant charge conditions. The normal charge case included the following: total refrigerant charge, local void fraction calculations for the heat exchangers (to find refrigerant distribution in the system), and computing the opening of the expansion valve from the liquid-gas flow ratio at the inlet to the expansion valve. The simulation was then expanded to include reduced refrigerant charges.

The computer model was compared to actual operating data (components were not described) and good agreement was found (figures with simulation and test data were shown in the paper that indicated agreement within ±5%).

FDD Results

The expansion valve was found to compensate for lower refrigerant charges until only a 60% charge was left. At that point, the expansion valve was fully open and any further refrigerant loss also resulted in dramatically lower refrigerant flow rates. The authors argue that only the liquid-gas ratio measurement provides consistently sensitive measurements to detect refrigerant loss under various loading conditions. As long as the ambient temperature was greater than 20°C (68°F), the proposed method could detect a 40% loss of refrigerant.

Inatsu, H., H. Matsuo, K. Fujiwara, K. Yamada, and K. Nishizawa, 1992, "Development of Refrigerant Monitoring Systems for Automotive Air-Conditioning Systems," *Society of Automotive Engineers*, SAE Paper No. 920212.

2.2.3 A Fault Diagnosis System for District Heating and Cooling Facilities

Authors: T. Kumamaru, T. Utsunomiya, Y. Yamada, Y. Iwasaki, I. Shoda, and M. Obayashi

Overview

A fault diagnosis scheme composed of a cause-effect tree diagram is used to find the causes of faults in a District Heating and Cooling Facility (although the main equipment under consideration is a heat pump used as a chiller). Only some of the faults studied were mentioned, such as: "reduced capability of heat pump", "high pressure of condenser", "tube dirt of condenser", "pressure down of river water", and "output down of inverter".

FDD Method

Characteristic curves were developed of the heat pump performance as a function of cooling water temperature and loading. The calculations for detection and diagnosis overlap and are executed simultaneously. The method is essentially an expert system and emphasis is placed in describing its operation and how it interfaces with human users. Diagnoses of faults are made based on the size of residuals as compared to reference points.

FDD Evaluation

The method was applied to an industrial plant. Evaluation proved difficult because of wide variations in operating conditions during different seasons. The operators then looked at the trend data and apparently defined fault thresholds based on the magnitudes of each sensor's variation.

FDD Results

Many of the fault thresholds were set at a level of 15% for a symptom classification and 20% for a fault classification.

Kumamaru, T., T. Utsunomiya, Y. Yamada, Y. Iwasaki, I. Shoda, and M. Obayashi, 1991, "A Fault Diagnosis System for District Heating and Cooling Facilities," *Proceedings of the International Conference on Industrial Electronics, Control, and Instrumentation,* Kobe, Japan (IECON '91), Vol. 1, pp. 131-136.

2.2.4 A Statistical, Rule-Based Fault Detection and Diagnostic Method for Vapor Compression Air Conditioners

Authors: Todd M. Rossi and James E. Braun

Overview

This paper describes the development and evaluation of a method for detecting and diagnosing faults in air-conditioning equipment that only requires temperature and humidity measurements. The diagnostic approach is based on generic rules and does not require equipment specific experimentation. Thresholds for both fault detection and diagnosis are based upon statistical analysis of on-line measurements. Five distinct faults were considered. The impact of the number of sensors on the sensitivity for detecting and diagnosing refrigerant leakage was also studied. The performance of FDD methods for this study was evaluated using a combination of simulations and laboratory experiments.

FDD Method

In this investigation, the performance of the cycle was characterized using a vector of temperature measurements only.

The preprocessor portion of the FDD system contains two major components: a steady state model and the preprocessor portion of a steady state detector. The steady state model was a lookup table that produced perfect predictions of plant output measurements when given the correct measured inputs. The steady state detector's preprocessor evaluates the variation in the output measurements for use by the 'classifier'. The FDD system will only indicate a fault and provide a diagnosis when the system is in steady state. The classifier consists of fault detection, diagnostic, and steady state classifiers.

Faults are indicated when the classification error (the overlap of the normal and current distributions) is small enough for the false alarm rate to be acceptable. An optimal linear classifier was used for estimating the classification error associated with current and normal distributions of residuals. In this study, a fault was indicated whenever the classification error was below a threshold equal to 0.001. This threshold for classification error gives a small false alarm rate and was found to provide acceptable fault detection sensitivities.

Fault diagnosis is performed using the residual features as inputs to a rule-based classifier. These rules were developed and tested through simulation over a range of operating conditions and tested using experiments at a single operating point. The overlap of the current distribution with each of the modeled classes is calculated and represents the probability that the fault class is correctly diagnosed. A diagnosis is indicated when the probability (overlap) of the most likely class is larger than the second most likely class by a specified threshold. The overlap is evaluated by integrating the area under the m-dimensional Gaussian probability distribution that falls within each class' region of the domain.

In this study, the calculation of the overlap within each class is simplified by assuming that each dimension is independent. A diagnosis was considered valid when the probability of the most likely class was more than double that of the second most likely class.

FDD Evaluation

A fully-instrumented, 3-ton rooftop air-conditioner was used for testing FDD algorithms. The system had fixed-speed condenser and evaporation fans, a fixed orifice expansion device, and a single-stage, on/off controlled reciprocating compressor.

The faults considered and the manner they were simulated were:

1. Condenser fouling: paper was placed on the air-side of the coils
2. Evaporator filter fouling: paper was placed on the air-side filter
3. Leaky compressor valves: represented using a hot gas bypass line with a manual valve
4. Liquid line restriction: a manual valve was located in the liquid line before the expansion device
5. Refrigerant leakage: refrigerant charge removal was controlled by a valve located on the high pressure side of the unit and monitored with a scale

Seven temperatures were considered: evaporating temperature, suction line superheat, condensing temperature, liquid line subcooling, hot gas line or compressor outlet temperature, air temperature rise across condenser, and air temperature drop across evaporator.

A modular, steady state model that solves mass, energy, and momentum balances for any set of entering air conditions was used for simulation. Outputs of the detailed physical model were used to represent the plant during the simulation studies. Sensors were modeled by adding zero mean, independent, and identically distributed Gaussian noise to known values of the plant inputs and model outputs.

The variances of input and output measurements were modified by combining the estimated variance and the specified accuracy as if they were independent. Sensor noise was propagated through the steady state preprocessor using a first-order Taylor series about the known operating point.

FDD Results

Simulation results showed that:

- Compressor suction valve leakage is indicated when the efficiency is reduced by 5%.
- A simulated liquid line restriction is not detected until the diameter of the valve opening is reduced by about 80%. The insensitivity of FDD system to this fault was explained as follows. The restriction is modeled as a decrease in the diameter of the pipe just before the expansion device; therefore, the restriction is not noticeable when it is much larger than the expansion device opening.
- For condenser fouling, a fault is indicated when the flow rate is reduced by 20%, whereas the evaporator flow rate must be reduced by 40% before a fault is detected.
- In the case of refrigerant leakage, the FDD system detected changes of less than 2% in refrigerant charge.

The study did not consider the effect of modeling errors on the sensitivity of the FDD method. Future studies should look into modeling errors, which reduce sensitivity.

Rossi, T.M. and J.E. Braun, 1997, "A Statistical, Rule-Based Fault Detection and Diagnostic Method for Vapor Compression Air Conditioners," *International Journal of Heating, Ventilating, and Air Conditioning and Refrigerating Research*, Vol. 3, No. 1, pp. 19-37.

2.2.5 Failure Detection Diagnostics for Thermofluid Systems

Authors: J. Wagner and R. Shoureshi

Overview

The paper presents experimental results for a failure detection method used to assist in the diagnosis of heat pump failures. A model-free limit and trend checking scheme, and a model-based innovations detector are operated in parallel to detect faulty behavior.

The paper distinguishes failure detection schemes as either model-free or model-based methods. Model-free schemes include limit checking, redundant hardware-based voting, frequency analysis, and expert systems. Model-based techniques use dynamic modeling, modern control theory, advanced process diagnostics, and statistical decision theory. In nonlinear systems, variable structure systems are becoming viable alternatives to observed design methods.

FDD Method

A limit and trend checking scheme was implemented to track the system's output and see if it violated the specified operating ranges; moreover, an innovation-based failure detection method was also used. The innovation-based diagnostic required a process model, state variable observer or filter, and detection processor. The detection system is often composed of three steps:

1. Innovation generation determines the difference between the model estimates and actual system states
2. Data transformation takes the innovations and converts them into useful statistical properties
3. Decision making compares the information to threshold limits to check whether a failure has occurred

The measured inputs were the compressor power, compressor shell temperature, and condenser superheat.

The innovation-based failure detection scheme was built upon a compressor and superheat condenser model and used in conjunction with a variable structure system observer to analytically estimate the system performance.

FDD Evaluation

A small heat pump consisting of a compressor, condenser, capillary tube, and evaporator was used in the application of the developed FDD method. The signals were sampled every 15 seconds, and the first 2 minutes of operation were ignored to eliminate start-up transients. The innovation-based observer does not start collecting data until an absolute error checker approximately reaches zero, afterwards another 5 minutes is required to build its database.

The simulated faults were:

1. Condenser fan motor failure
2. Evaporator fan motor failure
3. Capillary tube blockage
4. Compressor piston leakage
5. Seal system leakage

FDD Results

The above five faults were detected at various times and using different detection methods, which are summarized in Table 2.5.

Table 2.5 Results from fault introduction into heat pump

Fault introduced	Detection scheme	Detection time (minutes)
Condenser fan motor failure	Innovation	2:00
Evaporator fan motor failure	Limit checking	4:00
Capillary tube blockage	Innovation, trend checking	0:45
Compressor piston leakage	Trend checking	0:30
Seal system leakage	Limit checking	1:00

The condenser fan failure and the blocked capillary tube were singled out for more detailed explanations via figures of measurement trends.

The thresholds for detection are given, but how they were determined is not fully explained. The innovation-based detector suffers from the inability to monitor the system at start-up because it must wait for convergence requirements and the collection of statistical samples. The faults introduced were all abrupt.

Wagner, J. and R. Shoureshi, 1992, "Failure Detection Diagnostics for Thermofluid Systems," *Journal of Dynamic Systems, Measurement, and Control*, Vol. 114, No. 4, pp. 699-706.

2.2.6 Effective Diagnosis Methods for Air-Conditioning Equipment in Telecommunications Buildings

Authors: Masataka Yoshimura and Noboru Ito

Overview

The paper discusses work done to implement a fault detection and diagnosis method in packaged air-conditioning systems.

FDD Method

A rule-based method was used with the thresholds defined as fuzzy variables.

Measurements used for diagnosis were:

1. High pressure coefficient (actual condensing pressure compared to rated pressure)
2. Low pressure coefficient (actual evaporating pressure compared to rated pressure)
3. Condenser cooling water (or air) temperature difference
4. Condenser water (or air) approach temperature

5. Superheat into the compressor
6. Subcooling
7. Air temperature difference across evaporator

FDD Evaluation

Only an experimental analysis was conducted, but no detailed information was presented.

FDD Results

No results for the thermal system were presented, but the paper included a figure showing results from FDD testing on pumps using a vibration meter.

Yoshimura, M. and N. Ito, 1989, "Effective Diagnosis Methods for Air-Conditioning Equipment in Telecommunications Buildings," In *Proceedings of IEEE INTELEC 89: The Eleventh International Telecommunications Energy Conference*, October 15-18, 1989, Centro dei Congressi, Firenze, Vol. 2, 21.1: 1-7.

2.3 Other HVAC System and Subsystem Applications

2.3.1 Fuzzy Model Based Fault Diagnosis

Author: Arthur L. Dexter

Overview

A parameter estimation approach to developing explicit fuzzy reference models is used to describe the symptoms of both faulty and fault-free operation. The reference models are generated from training data that is produced from computer simulation of a typical plant. The diagnosis uses a fuzzy matching scheme to compare the parameters of a fuzzy partial model. The reference models are also compared to each other to determine the ambiguity that occurs at some of the operating points. The fuzzy method of diagnosis has been developed to detect and isolate faults in air conditioning systems. The two faults studied were in the mixing box of an air-handling unit. The first was called the RETURN fault and it pertained to the incorrect commissioning of the actuator that controls the return dampers such that they opened when the inlet and exhaust dampers opened. The second fault was called the LEAK fault, which represented excessive leakage through the dampers when the damper was commanded to close fully.

FDD Method

The fuzzy reference models are composed of IF-THEN rules that describe the symptoms of faulty and fault-free operation. Each model is composed of many elements that represent the credibility (or confidence) that the associated rule correctly describes the behavior of the system around a particular operating point. The fuzzy reference model is based on training data collected from computer simulation or expert knowledge. A partial fuzzy model is developed from operating data collected from a real plant.

The similarity between the partial fuzzy model and reference model is calculated as follows:

$$Sim_{Sp,Si} = \frac{\sum_{n=1}^{N_r} MIN\{C_{Sp}(n), C_{Si}(n)\}}{\sum_{n=1}^{N_r} C_{Sp}(n)}$$

where C_{Sp} represents the credibility of the *n*th rule of the partial fuzzy model and C_{Si} is the credibility of the equivalent rule in the *i*th fuzzy reference model.

Since some fault conditions will have common symptoms at particular operating points, it is necessary to compare the reference models to determine their ambiguity in identifying faults at those locations. Once the ambiguity is found (denoted by Amb_{Si}), it is used in the following equation:

$$m(\{S_i\}) = \frac{\sum_{n=1}^{N_r} \{MIN\{C_{Sp}(n), C_{Si}(n)\} - Amb_{Si}(n)\}}{\sum_{n=1}^{N_r} C_{Sp}(n)}$$

where m({S}) is the measure of the unambiguous strength of evidence that the system is in the particular operating state S.

FDD Evaluation

The detection of faults in the mixing box of an air-handling unit was used to demonstrate the practical application of the method. Three sets of multivane dampers are moved by independent motors to achieve the desired amount of fresh air entering the building while maintaining a constant flow of air to the building. Two faults that can lead to incorrect operation of the mixing box were considered in this paper. The first was called the RETURN fault, a problem that arises in the incorrect commissioning of the actuator that controls the return dampers such that they open when the inlet and exhaust dampers open. The second fault was called the LEAK fault, which represented excessive leakage through the dampers when the damper should be fully closed.

The rules developed for the fuzzy model relied on a normalized supply temperature measurement. In order for this temperature to be valid, the heating and cooling coils in the air handling unit must remain off, thereby causing the relationship between the supply, ambient, and return temperatures to be linearly dependent. Three measurements were used at 6 levels each, resulting in a total of 216 possible rules. These measurements were the previous normalized supply temperature, the previous damper position (assigned as 1 while fully open and 0 when fully closed), and the current normalized supply temperature. The fuzzy reference sets that describe these three measurements were all simulated as overlapping triangular functions with peaks at each of the 6 levels.

The ambient temperature and return temperature were held constant at 10°C (50°F) and 20°C (68°F) respectively during the test. A control signal was fed to the damper actuator beginning at 1 and varying at the speed of the actuators randomly throughout the control spectrum until 0 was finally reached—taking approximately 1100 minutes. The sampling interval for these tests was 30 seconds.

FDD Results

To understand the differences in the symptoms between correct and faulty behavior, the simulated plant that had generated the training data was also used to generate the test data. The results are presented as a percentage of belief in a particular condition as shown in Table 2.6.

Table 2.6 Levels of belief from the simulated test data

Test Condition	Level	RETURN fault	LEAK fault	Fault-free
No fault	Lower bound	0%	0%	57%
No fault	Upper bound	21%	40%	100%
Return fault	Lower bound	22%	0%	0%
Return fault	Upper bound	100%	71%	60%
Leak fault	Lower bound	0%	10%	0%
Leak fault	Upper bound	48%	100%	78%

This data shows that the symptoms of a leaky damper are nearly indistinguishable from those of fault-free behavior over most of the operating points. Furthermore, the symptoms of the return fault are very similar to correct operation over the limited operating range where the return fault is present.

When data was collected from an experimental air-handling unit that was believed to be operating correctly, the results given in Table 2.7 were achieved.

Table 2.7 Levels of belief from experimental test data

Level	Return fault	LEAK fault	Fault-free
Lower bound	0%	0%	59%
Upper bound	14%	35%	100%

The results are very close to those obtained with the simulated test data.

The sensitivity of the diagnosis to the type of reference model used is still under analysis. The goal is to produce generic reference models (Dexter 1996, A Generic Approach to Identifying Faults in HVAC Plants).

Dexter, A.L., 1995, "Fuzzy Model Based Fault Diagnosis," *IEE Proc.-Control Theory Appl*., Vol. 142, Pt. D, No. 6, pp. 545-550.

2.3.2 A Generic Approach to Identifying Faults in HVAC Plants

Authors: Arthur L. Dexter and Mourad Benourets

Overview

The paper presents a semi-qualitative model-based method of fault diagnosis. Generic reference models are used to describe fault-free and faulty operation in a generic system. A 'partial model' is identified on-line from the measured data and compared with the reference models. Credibility, similarity, ambiguity, strength of the evidence, and the degree of belief are generated. The degrees of belief are subsequently used to detect and diagnosis faults.

FDD Method

The fuzzy-model-based fault-diagnosis scheme identifies faults by comparing a partial model that describes the current behavior of the system with a set of generic reference models. One of the reference models describes the correct operation of the system and each of the other models describes the behavior of the system in the presence of a particular fault. The reference models were established with the data produced by simulating a number of plants of the same type as the plant under test. The partial model is identified on-line from the measured data using a numerically simple fuzzy identification scheme. The rules of the partial model are then compared to the rules of the fuzzy reference models using a fuzzy matching scheme with the following procedure.

The degree of similarity $S(R_p,R_i)$ between the partial model (R_p) and any one of the reference models (R_i) is calculated with the credibilities of the rule in the partial model and the reference model. The degree of similarity $S(R_p,R_i, R_j)$ of the partial model and two of the reference models (Ri and Rj) is also calculated.

The ambiguity $\lambda_{Ri}(n)$ associated with the *n*th rule of the partial model and the reference model R_i and the *n*th rule of all of the other reference models is calculated. Similarly, the ambiguity $\lambda_{Ri,Rj}(n)$ associated with the *n*th rule of two reference models, R_i and R_j and the *n*th rule of all the other reference models is calculated. Then the total ambiguity Λ_{Ri} associated with the reference model R_i is calculated.

The strength of the evidence m({Ri}) that the system is in the state described by the reference model R_i is calculated with $S(R_p,R_i)$ and Λ_{Ri}. In the same way, the degree to which the partial model is only similar to both R_i and R_j is used to estimate the strength of evidence that the system is in either the state associated with model R_i or the state associated with model R_j.

Because of the sufficiently long interval between the current and last identification of the partial model, the new evidence (m_{new}) is combined with evidence collected previously (m_{old}) to generate the combined evidence.

The degrees of belief, *Bel*, that the system is in a particular state, R_i, R_j or (R_i,R_j) are then calculated from the combined evidence.

The most recent values of belief are either displayed to let the plant operator make final diagnosis, or the fault is identified and an alarm is sounded when the associated value of belief reaches a user-defined threshold.

FDD Evaluation

Experiments have been performed using a detailed nonlinear dynamic simulation of a variable-air-volume (VAV) air-conditioning system. Two types of degradation faults, waterside fouling and valve leakage, are introduced. The generic reference models were identified off-line using input/output training data generated by computer simulation. Test data are collected every 15 seconds throughout the occupancy period on a typical summer day at the following five operating conditions:

1. Normal system operation
2. 0.2mm buildup of scale at water side
3. 1mm buildup of scale at water side
4. 1% leakage through the cooling coil valve
5. 3% leakage through the cooling coil valve

Every model (generic reference model and partial model) is a qualitative description of the steady state relationship between the inputs and outputs with the same structure. The inputs are the valve control signal, the normalized air mass flow rate, and a variable that indicates if the coil is wet or dry. The output is the air side approach temperature.

FDD Results

Although the test results are ambiguous, the diagnosis does generate a reasonably high belief in either correct or leaky operation and a low belief in all of the other operating states when the system was operating correctly.

"The correct diagnosis is made when faults are introduced that have the same magnitude as those used in the generation of the reference models." The diagnosis generated a high, unambiguous belief in fouling when there is a 1mm-buildup scale and there is a significant belief in leakage when there is 3% leakage through the valve.

Method Assessment

The method gives good results when the fault in the system is of the same magnitude as those used in the generation of the reference models. For the evaluation process presented in the paper when two fault conditions were considered, the method is computationally efficient. However, the tests presented in this paper (fault type, fault severity, etc.) are somewhat limited. The HVAC subsystem tested in the paper is simple with ambiguous results. It is necessary to apply the method to more complex systems with more fault types.

The author did not mention how to calculate the credibilites of the partial and reference models. Neither did the author mention whether or not more reference models were necessary if more levels of the same kind of fault would be considered and whether this would affect the calculation of the credibilities.

Dexter, A.L. and M. Benouarets, 1996, "A Generic Approach to Identifying Faults in HVAC Plants," *ASHRAE Transactions*, Vol. 102, Pt. 1, pp. 550-556.

2.3.3 Monitoring and Fault Detection for an HVAC Control System

Authors: Paul S. Fasolo and Dale E. Seborg

Overview

This paper applied a fault detection technique for the online monitoring of feedback control systems—"controller performance index"—to the monitoring and fault detection of an air duct heating coil. Simulation results were demonstrated for this approach.

FDD Method

The 'performance index' provides a measure of how close the performance of an existing control system is to that for an optimal controller. The normalized performance index, η, which characterizes the controller performance relative to minimum variance control, is defined as follows:

$$\eta = 1 - \frac{\sigma_{mv}^2}{mse[y(i)]}$$

where y(i) is the control error, mse[y(i)] is the mean square error, and σ_{mv}^2 represents the variance of the forecast error. The forecast of the controller is given by:

$$u(i) = -G_c(B)(Y(i) - Y_{sp}(i))$$

where $Y_{sp}(i)$ is the set point and G_c is the transfer function (assuming a linear feedback controller).

The evaluation of the performance index can be estimated recursively online by replacing the unknown population variances by the current sample variances obtained with a recursive least square (RLS) method.

The fault detection strategy updates the estimate of the performance index via RLS at each sampling instant. The estimate is then compared to its confidence limits.

FDD Evaluation

The FDD method was evaluated in an extensive simulation study of a hot water heating coil for an air duct. The control objective is to regulate the exit air temperature by adjusting the hot water inlet temperature via a control valve on the hot water line and a standard proportional-integral (PI) feedback controller. This control problem has one controlled output variable (the exit air temperature), one adjustable input (the normalized valve position), and three disturbances (the inlet air temperature, the mass flow rate of the air, and the inlet water temperature).

The static and dynamic models of the heating coil subsystem were presented in this paper. However, the paper did not present how the 'performance index' method is applied with the models except by presenting the simulation results shown in Table 2.8.

Table 2.8 Simulation experiments

Run number	Fault Conditions
N1	No fault; random measurement and process noise only.
F2	No fault; exponential increase in air mass flow rate to a new steady state value.
F3	Sticky control valve; signal to the valve must change by at least 0.2% of full valve span to move the valve stem.
F4	Water pump failure; step decrease in water flow rate.
F5	Outlet air temperature sensor falls from its support; exponential decrease in measured air temperature
F6	Sticky control valve: signal must change by at least 0.55% of full valve span to change the valve position; moreover, a ramp change in inlet air temperature occurs.

FDD Results

The estimated performance index for the base case condition with a constant forgetting factor tended to drift and exceeded the confidence limits—explained away as poor excitation conditions for the RLS estimation. Consequently, a series of small, randomly occurring set point changes were introduced in the subsequent simulations as a pseudo-random, binary sequence. The introduction of a variable forgetting factor greatly reduces the effect of the set point changes and allows the estimate to stay within the confidence limits.

The performance index stays within the confidence limit after the initial transient for the exponential increase in the air flow rate, with the exception of the last two set point changes. The sticky control valve also remained within the confidence limits except when a ramp input was used. Therefore, these faults are not readily detected.

Water pump failure and temperature sensor failure (i.e., the sensor support harness broke and the sensor fell to the air duct floor) can be detected quickly, but cannot be distinguished using the current proposed method.

Method Assessment

The sensitivity of the proposed diagnostic technique and that of a standard Statistical Quality Control approach have been compared. In general, the SQC approach was able to detect smaller faults than the controller performance index method. An important theoretical advantage of the 'performance index' method is that it is capable of distinguishing between faults and the effects of load disturbances, in contrast to standard SQC methods. Another advantage is that relatively little engineering effort is required to design and implement this diagnostic technique. In particular, neither a physical model nor extensive training is required. However, it is difficult for the proposed method to distinguish between different kinds of faults.

Fasolo, P.S. and D.E. Seborg, 1995, "Monitoring and Fault Detection for an HVAC Control System," *International Journal of Heating, Ventilating, and Air-Conditioning and Refrigerating Research*, Vol. 1, No. 3, pp. 177-193.

2.3.4 Qualitative Model-Based Fault Detection in Air-Handling Units

Authors: A.S. Glass, P. Gruber, M. Roos, and J. Tödtli

Overview

The feasibility of a qualitative approach for detecting faults in a multi-zone variable air volume air-handling unit is considered in this paper. A class of faults in which dampers or valves suffer partial mechanical blockage is investigated. The operating modes of the sequential controller for the central air-handling plant are matched to a corresponding qualitative classification of steady state temperatures. Observed mismatches indicate the presence of faults. Trials of the method in an air-conditioning test laboratory are reported.

FDD Method

First, the temperature and pressure measurements are obtained and fed into a steady state preprocessor. The steady state preprocessor computes a geometrically weighted running variance with respect to a geometrically weighted running average for every measurement and compares the variance with some preset threshold. Only if all the measurements are at steady state is the system deemed to be in steady state.

Secondly, the controller outputs are converted to some predefined qualitative values (e.g., 'closed', 'not closed', 'maximally open', 'minimally opened' and 'between'). At the same time, the temperature measurements are input to a model-based predictor that outputs the predicted controller qualitative values at steady state conditions.

Faults are thus detected on the basis of discrepancies between the measured qualitative controller outputs and the corresponding model-based predictions based on temperature measurements. Usually, faults will be detected on points at the transition states when the measured qualitative controller outputs are different from the expected ones.

During analysis the model-based predictor takes advantage of 'landmarks', the transition states of the controller. The landmarks divide the whole operation range into some qualitatively different phases of control based on the measured temperatures. The temperature states corresponding to the landmark values must be modeled accurately. Although this aspect of the analysis is quantitative, the model is simple enough to be considered qualitative as a whole.

The controller signals for preheating coil, dampers, and cooling coil are collected. Measurements are also taken of the outside air, supply air, and return air temperatures. The airflow rate is calculated via the pressure difference.

FDD Evaluation

Simulation tests have been carried out using a SIMULINK model of a simplified variable air-volume system, which consisted of a central air-handling unit (CAHU). Experimental tests were also conducted on a laboratory air-handling unit with a similar CAHU system. The CAHU comprises a bypass mixer and a heating coil followed by a cooling coil in a single air duct. The task of the CAHU is to supply air at a controlled, fixed temperature, T_S, by operating the preheating coil, dampers and cooling coil in sequence. The controller must respond to three quantities over which it does not have control: ambient temperature, return-air temperature, and air flow rate (which are regarded as disturbances in this control loop).

To simulate partial mechanical blockage, the operating ranges of the three components in the CAHU were constrained to less than their full range.

The operating regimes of the CAHU sequential controller are modeled. Five different qualitative controller states are defined according to five qualitative temperature states in normal conditions. For example, when the outside air temperature is comparatively low, the qualitative controller state is 'dampers set for minimal outside air and controller operates heating coil'. When the mixed temperature of outside air and return air equals the supply air set point, the qualitative controller is 'heating and cooling switched off and controller operates dampers in normal mode'. Hence, there is a characteristic curve of outside air temperature vs. controller state. The transition points between different states are quantitatively modeled.

As the faults were introduced, the measured controller's qualitative signals deviated from the predicted ones. The symptoms of each certain fault were analyzed and a rule-table was compiled to aid diagnosis.

The measured controller's qualitative signals are compared to the corresponding model-based predictions based on temperature measurements. When they are at different states, a fault is detected and the rule-table is used to diagnosis the fault.

FDD Results

Symptoms arising from single faults can be detected. However, if multiple faults are assumed, the expected qualitative symptoms cannot normally be determined. The sensitivity of this method was not investigated and no detailed results were given.

Glass, A.S., P. Gruber, M. Roos, and J. Tödtli, 1995, "Qualitative Model-Based Fault Detection in Air-Handling Units," *IEEE Control Systems Magazine*, Vol. 15, No. 4, pp. 11-22.

2.3.5 Condition Monitoring in HVAC Subsystems Using First Principles Models

Authors: Philip Haves, Timothy I. Salsbury, and Jonathan A. Wright

Overview

This paper presents a condition-monitoring scheme that includes first principle (physical) models and a radial basis function (RBF) network for fault detection and diagnostics (FDD). The physical model is generally nonlinear in some of its fault parameters, so analytical techniques cannot be used to determine the optimum values during training. The RBF, which is linear in the parameters, is thus included to estimate a rich data set for model training. The outcome of the physical model was compared with on-line measurement for fault detection and diagnosis. In this paper the method is applied to the detection and diagnosis of coil fouling and valve leakage in a cooling coil.

FDD Method

The first principle models represent the principal static characteristics of the system. Some of the parameters of the model, which are physically meaningful and represent a tangible measure of system performance and thus are relatively easy for users to determine the detection thresholds, are generally nonlinear in the model. This characteristic made it difficult to locate the optimum parameters by analytical techniques. Box's complex direct-search method, which does not require derivative information, has therefore been adopted for the search. The objective function used is the mean of the squares of the errors (MSE) of the physical model.

The RBF model is included because direct estimation of the parameter values might converge to a local minimum, the use of the RBF enables data to be generated over the range of operation and helps to make the nonlinear optimization more robust. In order to calculate the MSE, the RBF model is used to generate outputs at points distributed uniformly within the input space and the outputs are compared with the outputs of the physical model. The optimum fault parameters are then searched to minimize the MSE. The difference between the prediction of the correct operational physical model and the measured output of the system are used to indicate the presence of faults.

FDD Evaluation

For the first principle models of the cooling coil system, the NTU effectiveness model was used as the coil model and a modified exponential function model was used as the valve model. The output of the first principle model was the airside approach, which was compared with the measurement to detect and diagnosis faults. Four parameters are required for the combined model: the mass flow rate of water into the coil, a valve model curvature parameter (c), a valve model leakage parameter (*l*), and the overall heat transfer conductance (UA). Design information and manufacturers' performance data were used to produce initial estimates of the parameter values. Training data collected when the plant was deemed to be operating correctly were then used to estimate the parameter values.

During operation of the scheme, the parameters UA and *l* were updated to provide the best fit to the data from the RBF. The RBF model wa constructed to approximate the multidimensional surface using Gaussian functions. A number of Gaussian functions were centered at selected positions within the input space and widths were selected so that the functions overlap. The output of the model was the sum of the Gaussian functions multiplied by the corresponding weights. The RBF model was initialized by training data generated from the calibrated physical model and was updated using a normalized least mean squares estimation technique. The outputs of the RBF model were then compared with the estimated parameter values to generate the optimum parameter values.

A transient detector was used to prevent updating the RBF at transient state by comparing the averaged absolute change of each variable from one time step to the next. In this case, updates were done only when the threshold was not exceeded. However, another threshold limit checking system was employed to avoid estimator windup by only updating the RBF when the difference between the predicted and measured outputs exceeded a certain threshold (indicating that the performance of the system had changed). Although not explicitly stated in the paper, it is assumed that the RBF was updated only when both limit checking schemes were 'true'.

The method was applied to test three fault cases: 3% flow rate leakage through the control valve, 1mm of calcium carbonate fouling on the tubes and both faults present at the same time

FDD Results

"The difference between the prediction of the correct operational physical model and the measured output of the system gives a good indication of the presence of a fault. For the fouling faults, the residual is positive at high coil duty, whereas for the leakage faults, it is negative at low duty. The correlation between the nature of the residual and the type of fault can be exploited for fault diagnosis." "The comparison of the UA values indicates a modest but significant reduction when the coil is fouled… A similar, but more subtle, effect is observed for the leakage parameter."

Method Assessment

The paper presents a way to handle the optimization of nonlinear parameters in the models.

The test result of the method presented in this paper is unclear. The deduction of UA or *l* when faults are introduced is hard to distinguish. The author left the detection and diagnosis threshold to be decided by users and thus did not give any analysis of FDD sensitivity and false alarm rate.

Haves, P., T. Salsbury, and J.A. Wright, 1996, "Condition Monitoring in HVAC Subsystems Using First Principles Models," *ASHRAE Transactions*, Vol. 102, Pt. 1, pp. 519-527.

2.3.6 Experiences With Process Fault Detection Methods Via Parameter Estimation

Author: Rolf Isermann

Overview

The paper focuses on fault diagnosis based on process parameters. The procedure consists of parameter estimation, feature extraction, fault decision and classification. Experimental results are given for several faults in a centrifugal pump and steam-heated heat exchanger.

FDD Method

One has a choice of choosing more sensors or developing a more complex model when more faults are to be detected. Choosing more sensors typically leads to non-robust measurements and higher sensitivity to sensor failure.

Fault diagnosis based on parameter estimation starts with data processing. After the signals have been filtered they are used for fault detection based on comparisons to a normal process. Once a fault has been detected, the features and their changes are used to diagnose the fault (sometimes fault detection and classification are merged into one step).

Process model parameters are understood as constants or time-dependent coefficients. These parameters appear in the mathematical description of the process as the relationship between the input and output signals.

The following procedure was developed to determine the process coefficients and their changes:

1. Establish a theoretical process model for measuring input and output signals
2. Determine the relationship between the model parameters and the process parameters
3. Estimate the model parameters based on measured signals
4. Calculate the process coefficients
5. Determine the change of the process coefficients with reference to normal values
6. Make a fault decision based on the process coefficient changes
7. Classify the fault to determine type, location, and size

This particular fault detection requires theoretical process modeling, parameter estimation of continuous-time models, and statistical decision and classification.

FDD Evaluation

A model was developed of a d.c. motor driving a centrifugal pump which circulated water (9 process coefficients were found). The model was trained under normal operation. Subsequently, 19 artificially generated faults were simulated and the process coefficients that changed were tabulated (detailed numbers were not provided). Only a few of the faults were explained, another paper is referenced to obtain a full explanation.

The parameter estimation technique was then applied to a steam-heated heat exchanger, a process that cannot be modeled with a high degree of accuracy as compared to the earlier example. The system contained a steam generator, steam-condensate circulation, water circulation, and a cross-flow heat exchanger to transport heat to the air. The mass flows of the steam and water, as well as the inlet and outlet temperatures of the fluid were measured. The outlet temperature was considered an output; the other three variables were inputs. It is not possible to determine all the process coefficients uniquely; therefore some have to be assumed as known.

The training of the model was accomplished using 60 transients for each of the 3 transfer functions. The artificially generated faults were:

1. Air (inert gas) in the steam space
2. Opened condensate valve
3. Closed condensate valve
4. Plugged tube

In the case of the faults, 30 transients were used for each transfer function. A total of 540 experiments were conducted.

FDD Results

No detailed results were presented for the centrifugal pump (some figures are provided with no explanation).

Each of the four faults in the heat exchanger led to different changes in the parameter estimates. The process coefficients are sensitive to changes of the process parameter estimates and to the values of the assumed coefficients. Hence, detailed theoretical modeling is not necessary (the theoretical model did not match the normal case very closely). All four faults can be detected using patterns of changes for each of the transfer functions. Values are given for the parameter estimates and some process coefficients of the steam flow changes (there is substantial deviation between the normal state and each of the fault states presented). It is not known to what level the faults were introduced, so no sensitivity can be determined.

Isermann, R., 1987, "Experiences with Process Fault Detection Methods via Parameter Estimation." In S. Tzafestas, M. Singh, and G. Schmidt (Ed.), *System Fault Diagnostics, Reliability and Related Knowledge-Based Approaches* (Vol. 1, pp. 3-33). Dordrecht, Holland: D. Reidel Publishing Company.

2.3.7 Fault Direction Space Method for On-Line Fault Detection

Authors: Yi Jiang, Jisheng Li, and Xudong Yang

Overview

The Fault Direction Space (FDS) Method was presented for on-line fault detection of HVAC components or subsystems. Characteristic Parameters (CP) are used to indicate the abnormal state and a fault direction space was introduced with the variations of CPs as the coordinates to represent the knowledge of fault. The type of fault can then be distinguished by comparing the measured direction of the CP with the standard fault directions. An if-then reasoning procedure can then be replaced by multiplying the FDS matrix with the CP vector and thus the threshold can be avoided in the diagnostic process.

FDD Method

First, a group of characteristic parameters (CP) is established according to the physical model of the component/subsystem to be detected. The CP can be determined from the measured data, but should be dependent only on the structure of the component or subsystem itself and be operation-state independent. Therefore, the CP should appear constant during operation at the faultless state and deviate from the normal value when a fault occurs.

As an example, the paper addressed a primary/secondary loop heat exchanger. Two characteristic parameters were defined that could be computed in terms of measured inlet and outlet temperatures and pressures according to:

$$\varepsilon_1 = R_s / R_p = \frac{(T_{ps} - T_{pr})\sqrt{P_{ps} - P_{pr}}}{(T_{ss} - T_{sr})\sqrt{P_{ss} - P_{sr}}}$$

$$\varepsilon_2 = R_s C_p / US = \frac{\Delta T_{Ln}}{(T_{ss} - T_{sr})\sqrt{P_{ss} - P_{sr}}}$$

where:

- R_p, R_s = flow-resistant coefficients for primary and secondary sides of a water-water heat exchanger;
- Subscripts ps and pr = primary side supply water and return water, respectively;
- Subscripts ss and sr = secondary side supply water and return water, respectively.
- U = heat transfer coefficient between the two sides of the heat exchanger;
- S = effective area of the heat exchanger;
- P = pressure.

ε_1 and ε_2 were derived from heat transfer and flow relations. As can be seen, S and R are constant for a specified heat exchanger and U changes within a small range normally as the flow rate changes. Thus, ε_1 and ε_2 should be relatively constant in a fault-free state.

To classify faults, relationships between the deviations of each CP are employed in replacing the logic tree and thresholds in the normal reasoning procedure. If X1, X2, and X3 are a group of CPs, a three-dimensional FDS can then be constructed with D1, D2 and D3 (the deviations of CPs) as the coordinates. If there is a fault, then D1, D2 and D3 may deviate from zero; the direction of the three-dimensional vector (D1, D2, D3) will indicate the type of fault. For instance, in the example of the heat exchanger, dirt and scale will reduce the U-factor of the heat exchanger only, so that ε_2 will increase and ε_1 will not change. A blockage in the secondary loop can decrease R_s and thus increase both ε_1 and ε_2. However, since the flow rate goes down, the U-factor may also decrease and hence the increase of ε_2 will be greater.

To analyze the sensitivity of the method, the normal state region (NSR) around the origin in the FDS is introduced. The NSR separates the changes of the CPs resulting from factors other than system errors (e.g. the nonlinear effect of heat transfer coefficient, the dynamic influence of the system, and the sensor error) in the system from those that are errors.

To apply the method, sensors are installed on a heat exchanger to measure:

- P_{ps}/P_{pr}: the supply and return water pressures on the primary side,
- T_{ps}/T_{pr}: the supply and return water temperatures on the primary side,
- P_{ss}/P_{sr}: the supply and return water pressures on the secondary side, and
- T_{ss}/T_{sr}: the supply and return water temperatures on the secondary side.

FDD Evaluation

In this paper, the FDD method was applied to a plane water-water heat exchanger. The faults considered were:

1. Poor heat exchange performance due to dirt and scale
2. Leakage from the primary to the secondary loop through the heat exchanger
3. Blockage in the primary loop
4. Leakage from the primary loop to outside
5. Blockage in the secondary loop
6. Leakage from the secondary loop to outside
7. Stoppage of the secondary circulation pump

Simulations were carried out with a detailed dynamic model to discover the range of NSR. A random number producer simulated errors from the sensors. Normalization of ε_1 and ε_2 was performed to make the NSR uniform instead of system and operation-state dependent.

Detailed transient simulation (several levels for each type of fault concerned) was also done to discover the directional ranges for each fault type.

The procedure was applied in a district heating system to monitor heat exchangers in 40 substations. Controllers installed at each substation collected temperatures and pressures. Normalization was done at each time step. If a normalized CP larger than five was discovered, the match procedure was used to classify the type of fault according to the direction of the CP.

FDD Results

The analytical results for a special case of the FDS method's sensitivity are given in Table 2.9.

Table 2.9 Model sensitivity to various faults

	Poor performance	Block in primary loop	Block in second loop	Leak in second loop	Leak between primary and second loop
Sensitivity	>17%	>50%	>50%	>30%	>18%

Here sensitivity denotes that the method is sensitive to a certain kind of fault when the level of the fault becomes larger than the given sensitivity value.

Although the method had been applied in the field, the paper recorded no detailed results, only commenting that a number of fault cases have been properly reported during its operation.

There is no detailed reporting of the method on other HVAC components or subsystems and for the case of different faults having substantial overlap in the FDS.

Method Assessment

One of the major advantages of this method is that it can distinguish some faults by different ratios of CPs. However, this advantage may be limited to specified equipment, i.e., different ratios of CPs corresponding to different fault direction may change from unit to unit. Although the author stated that the on-line identification of a component or subsystem model—as required in most of the fault detection procedures—is not needed, there is still considerable work associated with CP determination and normalization. From the results presented in the paper, the method's sensitivity is poor.

Jiang, Y., J. Li, and X. Yang, 1995, "Fault Direction Space Method for On-line Fault Detection," *ASHRAE Transactions*, Vol. 101, Pt. 2, pp. 219-228.

2.3.8 Fault Detection in an Air-Handling Unit Using Residual and Recursive Parameter Identification Methods

Authors: Won-Yong Lee, Cheol Park, and George E. Kelly

Overview

Two methods—residual and parameter identification—were used for detecting faults in an air-handling unit. Faults were detected by calculating residuals from the comparison of the normal operating condition data with the measured data. Faults were also detected by examining immeasurable parameter changes in a model of the controlled system using a system parameter identification technique. In the last method, autoregressive moving average with exogenous input (ARMAX) and autoregressive with exogenous input (ARX) models with both single-input/single-output (SISO) and multi-input/single-output (MISO) structures were examined. The tests were done for only one load on the AHU and eight complete faults were detected.

FDD Method

Residual and parameter identification methods were employed in this paper for fault detection in an air-handling unit of a building HVAC system.

Residual values were defined as the differences between actual measured values under a fault condition and the expected values under normal operation. The residuals of the supply air temperature, the supply duct static pressure, the flow difference between the supply and return fans, the cooling coil control signal, the actuators and the cooling coil valve position were defined.

If some physical changes in the system cause deviations from the normal state, some or all of the parameters in a continuously updated model of the process will deviate from their normal values. The fault condition can then be detected. In this paper, the parameters of a model were estimated employing a system identification method with a typical recursive parameter identification algorithm. ARMAX and ARX models with MISO and SISO structures were employed to estimate model parameters recursively using the Kalman filter. The paper did not provide a detailed explanation of how the algorithm was applied to this application.

For both methods, the thresholds for every residual or model parameter were determined. If a measurement was greater than an upper threshold limit or was less than a lower threshold limit, the process was reported to be faulty. In this study, a three-sigma limit was used as the threshold value.

It is important to note that the system identification parameters may change with load changes. However, since the load conditions often vary much slower than the development of faults, the dramatic changes in the identification parameters can still indicate the presence of fault.

Faults were detected when residuals and identification parameters changed significantly and the thresholds were exceeded. Momentary indications of faults were ignored.

FDD Evaluation

The approach was applied to a variable-air volume (VAV) system. The unit consists of fans, dampers, a cooling coil, sensors, and controllers. A proportional-integral-derivative (PID) controller using the velocity algorithm was designed to control the supply air temperature. Two other controllers controlled the static pressure in the supply duct and the difference between the supply and return airflow rate.

To smooth the measured data and reduce the effect of random noise, smoothing filters were applied to the supply duct pressure, flow rate, and supply air temperature measurements.

Eight kinds of faults were considered:

1. A complete failure of the return fan;
2. A complete failure of the supply fan;
3. A complete failure of the chilled-water circulation pump;
4. The fault condition where the cooling coil control valve sticks in a certain position;
5. The case when a temperature sensor undergoes a complete failure;
6. A complete failure of the static pressure transducer in the air supply duct;
7. A failure of the supply fan flow station;
8. A failure of the return fan flow station.

These faults were examined using both residual and parameter identification methods using the laboratory-measured data. The work was done for only one load imposed on the AHU. The training process was only briefly mentioned.

FDD Results

The proposed FDD methods detected the presence of each of the eight faults considered. Each fault had a unique signature, which could be used for fault diagnosis, but was not further explored in the paper.

The comparison of ARMAX and ARX models showed that all the estimated values were close to each other for the case of a constant load on the AHU and no external disturbances.

Some comparisons were made between the two detection methods. The residual method required less computing time to calculate the residuals, but required more sensors than the parameter identification method.

Since all the faults were at only one level (complete failure), no sensitivity analysis was done. Moreover, different results might be obtained if the building loads change rapidly, because only one load on the AHU was considered. Also worthy of note is that the residuals of control signals were also utilized in this approach.

Lee, W.Y., C. Park, and G.E. Kelly, 1996, "Fault Detection in an Air-Handling Unit Using Residual and Recursive Parameter Identification Methods," *ASHRAE Transactions*, Vol. 102, Pt. 1, pp. 528-539.

2.3.9 Fault Diagnosis of an Air-Handling Unit Using Artificial Neural Networks

Authors: Won-Yong Lee, John M. House, Cheol Park, and George E. Kelly

Overview

This paper describes the application of artificial neutral networks (ANN) to the problem of fault diagnosis in an air-handing unit. Initially, residuals of system variables that can be used to quantify the dominant symptoms of fault modes of operation were selected. Idealized steady state patterns of the residuals were then defined for each fault mode of operation. An artificial neutral network using the back propagation algorithm learned the steady state relationship between the dominant symptoms and the faults. The trained neural network was applied to experimental data for various faults and successfully identified each fault.

FDD Method

Fault diagnosis can be thought of as pattern recognition and ANNs are well suited to this task. The approach used in this paper relies on the ability of an ANN to identify patterns of residuals that can be used as signatures for various faults. Through laboratory testing, it was determined that seven residuals are needed to identify the eight faults considered in this paper. Using a type of if-then reasoning, the matching of dominant residuals to the various faults is constructed as shown in Table 2.10 where –1, 0, and 1 denote decreases, no changes, and increases, respectively, in each of the residuals (R's).

Table 2.10 Normalized patterns for AHU fault diagnosis

Net Inputs							Net Outputs									Fault Diagnosis
R_p	R_q	R_t	R_u	R_{ns}	R_{nr}	R_v										
0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	**Normal**
-1	-1	0	1	-1	0	0	0	1	0	0	0	0	0	0	0	**#1 Supply fan**
0	1	0	0	0	-1	0	0	0	1	0	0	0	0	0	0	**#2 Return fan**
0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	**#3 Pump**
0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	**#4 Cooling coil valve**
0	0	-1	-1	0	0	0	0	0	0	0	0	1	0	0	0	**#5 Thermocouple**
-1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	**#6 Pressure transducer**
0	-1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	**#7 Supply flow station**
0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	**#8 Return flow station**

The ANN is then trained using data that are representative of the normal condition and of the various fault conditions. The inputs are normalized values of the residuals and the outputs are values that constitute a pattern that represents the normal mode or one of the fault modes of operation. Hence, input/output patterns are used to train the network. The trained ANN was then applied in a straightforward manner to detect the faults.

FDD Evaluation

A variable air-volume (VAV) air-handling unit (AHU) was utilized for this study. The static pressure in the main supply duct is maintained at the setpoint by sensing the static pressure and controlling the rotational speed of the supply fan. Modulating the cooling water control valve controls the supply air temperature. The variable speed return fan controls the airflow rate difference between the supply and return. A proportion-integral-derivative (PID) control algorithm controls the cooling water valve and proportional-integral (PI) control algorithms control the fan speeds.

The eight faults studied included:

1. Failure of the supply fan
2. Failure of the return fan
3. Failure of chilled-water pump
4. Stuck cooling coil valve
5. Failure of the supply air temperature thermocouple
6. Failure of the supply air pressure transducer
7. Failure of the supply fan flow station
8. Failure of the return fan flow station
9.

All faults were simulated in the laboratory AHU by either sending faulty control signals from the PC to an actuator or by overwriting the sensor's signals with faulty values. The pump fault was introduced by manually reducing the pressure of the cooling water supplied to the cooling coil.

Residuals were calculated using steady state values of the system variables measured 900 seconds after a fault was introduced. The dominant symptoms/residuals were analyzed and matched to each fault. The appropriate network topology and number of training periods were determined (through an extensive trial-and-error process) and the ANN architecture was built. Using the back propagation algorithm, the ANN was trained using data that were representative of the normal condition and the various fault conditions.

FDD Results

A perfect diagnosis of the ANN would yield a unity output variable corresponding to the fault introduced while the other outputs are zero. The experimental results were good since the corresponding variables were almost unity (from 0.927 to 1) while the other outputs were zero. The laboratory tests demonstrated that each of the eight severe faults in an AHU could be successfully diagnosed at steady state if introduced one at a time—only severe faults without noise were considered. Transient state and field tests have not been done. It is anticipated that ANNs would be effective for less severe faults because of their ability to generalize and to learn complex, nonlinear relationships.

Lee, W.Y., J.M. House, C. Park, and G.E. Kelly, 1996, "Fault Diagnosis of an Air-Handling Unit Using Artificial Neural Networks," *ASHRAE Transactions*, Vol. 102, Pt. 1, pp. 540-549.

2.3.10 Fault Diagnosis and Temperature Sensor Recovery for an Air-Handling Unit

Authors: Won Yong Lee, John M. House, and Dong Ryul Shin

Overview

This paper describes the architecture for a two-stage artificial neural network (ANN) for fault diagnosis and the use of regression equations for sensor recovery of failed temperature sensors. To simplify the ANN, the air-handling unit (AHU) was divided into several subsystems. The stage one ANN was trained to classify the subsystems in which faults are occurring, and the stage two ANN was trained to diagnose the cause of faults at the subsystem level. The trained ANN was applied to simulation data and shown to be able to identify the eleven faults considered. A regression equation was used to recover an estimate for the supply air temperature when the supply air temperature sensor yielded erroneous measurements. The estimates of the sensor measurement can be used for control purposes.

FDD Method

The method is developed with the assumption of steady state conditions; therefore, a steady state detector is used. Using least-squares regression, straight lines are fit through the recent and five previous values of the variables used in the steady state detector. If the absolute value of the slope of each is less than its associated threshold value, the system is deemed to be in steady state. The threshold value for the slope is approximately three times the value of the average slope for a particular variable under normal conditions.

A simplified dynamic model based on steady state characteristic equations and approximate first-order dynamics is used. Initial values of the damper positions, valve positions, and fan speeds are selected first. The pressure and air flow rate, the supply air temperature, the inlet and exit cooling water temperatures, and the control signals to the fans and the cooling coil valve are subsequently determined. Finally, the control signals are converted to the new values of the supply and return fan speeds and the cooling coil valve position. The solution procedure is then repeated.

Pre-defined residuals, the difference of measured and expected variables, are computed next. To compute the residuals of supply air temperature and the mixed air temperature, regression equations are used to estimate the current values for the normal operating conditions. The dominant symptom residuals for each different fault case are analyzed. Residuals are normalized so that the dominant symptom residuals have approximately the same magnitude for different cases.

To lessen the requirement for extensive computational resources, a two-stage ANN architecture was proposed. Stage one is used to classify the subsystem in which a fault is occurring. For example, in this study, the subsystem classifications are the pressure control subsystem, the flow control subsystem, the cooling coil subsystem and the mixing box damper subsystem. Stage two is used to diagnose the cause of a fault on the subsystem level.

The ANN is trained using patterns that are not ideal. Residuals that are ideally one are replaced with a random value taken from a uniform distribution ranging from 0.5 to 1 and those that are ideally zero with a random value taken from a uniform distribution ranging from 0 to 0.5. This approach enables the trained ANN to logically classify patterns that fall somewhere between idealized input patterns. Also, a filter that calculates a moving average of each ANN output value is used to suppress abrupt diagnoses.

The paper also presents a sensor recovery method when a critical temperature sensor is found to be faulty. The regression equation used to compute the expected value of the supply air temperature is used to recover an estimate of the supply air temperature when this sensor fails. Once the fault is diagnosed, the estimate of the supply air temperature is used in the feedback control loop to recover control of the actual supply air temperature. It is important to note that the sensor recovery is reasonable only if the inputs to the regression equations are correct.

FDD Evaluation

The two-stage ANN and the sensor recovery method were demonstrated using data obtained from a simulation model of a laboratory-scale AHU. Results based on experimental data are not presented in this paper. The AHU system consists of fans, dampers, a cooling coil, sensors, and controllers. Component models that were developed earlier have been modified to fit experimental data and subsequently became the simulation models.

Eleven faults were considered:

1. A complete failure of the supply fan.
2. A complete failure of the return fan.
3. A failure of a local feed water pump—causing the water flow rate to decrease; however, the flow rate is not zero because the main supply pumps are still operating.
4. A stuck cooling coil valve.
5. A complete failure of the supply air temperature sensor.
6. A second type of failure of the supply air temperature sensor. In this case, the sensor drops from its supporting harness onto the floor of the duct, giving an incorrect temperature reading.
7. A third type of supply air temperature sensor failure, due to sensor drift.
8. A failure of the supply air pressure transducer.
9. A failure of the supply airflow station. In this case, a zero reading is obtained for the supply airflow station.
10. A failure of the return fan flow station. In this case, a zero reading is obtained for the return fan flow station.
11. A failure of the mixing box damper linkage.

The stage one ANN had two hidden layers while the stage two had one. The networks were trained until the sum-of-squares error was less than 3. A commercial ANN software package was used for the training.

In the testing phase, data obtained from a simulation program based on simplified AHU component models were used as inputs. Faults were introduced through modification of the computer algorithm.

Three variables are used in the steady state detector: supply air temperature, supply air pressure, and the flow rate difference between the supply and return air ducts.

The stage one ANN classifies the subsystems in which the faults occurred: normal, pressure control subsystem fault, flow control subsystem fault, cooling coil subsystem fault, mixing box damper subsystem, and an unknown type of fault. The stage two ANN that was presented dealt with the cooling coil subset and diagnoses the following five conditions: normal, temperature sensor failure, temperature sensor degradation or pump failure, valve failure, and an unknown type of fault.

FDD Results

The results demonstrated the capability of the two-stage ANN to correctly diagnose the fault subsystem for 11 faults in the AHU and to further diagnose the faulty component for the 5 faults that occurred in the cooling coil subsystem.

The two-stage approach simplifies the generalization by replacing a single ANN that encompasses all considered faults with a number of less complex ANNs, each one dealing with a subset of the residuals and symptoms associated with a complete diagnosis of all faults.

It was also shown that using the outcome of the regression equation for the supply air temperature as the feedback signal to the cooling coil valve controller, the real value of the supply air temperature could be recovered to a value near the set point. The sensor recovery is valuable in the correct performance of controllers when certain faults take place.

Lee, W.Y., J.M. House, and D.R. Shin, 1997, "Fault Diagnosis and Temperature Sensor Recovery for an Air-Handling Unit," *ASHRAE Transactions*, Vol. 103, Pt. 1, pp. 621-633.

2.3.11 Development of a Fault Diagnosis Method for Heating System Using Neural Networks

Authors: Xiaoming Li, Hossein Vaezi-Nejad, and Jean-Christophe Visier

Overview

The paper presented the first step of a fault diagnosis method in complex heating systems with the application of artificial neural networks (ANN). A two-level ANN was constructed. Simulated data were used to train and test the ANN. Six operating modes with faults were considered and diagnosed correctly.

FDD Method

A detailed investigation in cooperation with heating system maintenance experts helped to identify the most important operating faults. The relevant parameters needed to distinguish the faults were chosen in the construction of the network's inputs. The choices stemmed from physical analysis and graphical analysis based on the generated database. There was no general rule for choosing the representing space.

The architecture of the ANN is determined through an iterative process. The number of input neurons is equal to one bias neuron (for the threshold) plus the number of components that code the training and the testing patterns in one specific representative space. As many neurons as the number of the classes to be discriminated are used as the ANN output. The number of layers between network inputs and the output layers and the size of the layers are up to the designer. To decide the number of neurons in the hidden layer of the ANN, a compromise was found between the neuron number and the sum-square error between the target outputs and the actual outputs of all the training patterns.

To train the ANN method, a database representing the different operating modes of the system with and without faults was generated. A back-propagation algorithm was used to train multi-layered feed-forward networks with a tan-sigmoid transfer function for performing pattern discrimination.

FDD Evaluation

In this paper, the ANN FDD method was applied to a simplified reference heating system. The building was representative of a middle-sized office building or school (2000m^2, five floors). The heat generation plant includes two classical gas-fired boilers. The secondary loop has two circuits, each of which has its own control system. A typical weekly occupation was assumed. The operation mode controller (OMC) distinguished four operation modes:

1. Stop heating
2. Reduce heating
3. Boost heating
4. Normal heating

The simulation of the building and its heating system was performed using commercial simulation software and a toolbox of HVAC components. The models of the toolbox include a dynamic representation of the different components. The simulation of the plant includes a detailed model of the control system: OMC, heating curve, and thermostatic valve. The simulation of the most important operating faults was used to construct the database for training and testing the ANN. The faults considered came from questionnaire results answered by maintenance experts. The following seven operating modes were considered:

1. Normal mode
2. Bad combustion in the boiler's burner. The fault of excess air rate was chosen to simulate this type of fault.
3. Dirtiness and scale formation in the boiler's heat exchanger. Simulated by changing the heat transfer coefficient.

4. Bad tuning of the heating curve in the radiator circuit. Implemented by lowering the supply hot water temperature, thus causing the heating curve to also be low.
5. Early boost.
6. Late boost.
7. Leaky valve.

Parameters believed to be pertinent to the faults considered were chosen to construct the network's input:

1. Flue gas temperature of boiler during the boost heating period
2. Room temperature from 10 a.m. to 6 p.m.
3. Room temperature at 6 a.m.
4. Room temperature at 8 a.m.
5. Water supply temperature from the beginning of the unoccupied period.
6. Daily outdoor temperature.
7. Length of unoccupied period.
8.

The seven inputs were normalized to make them numerically comparable.

After some unsuccessful attempts, a combination of two networks was chosen—ANN1 (discriminating the heating curve from the other classes) and ANN2 (discrimination classes other than the 'heating curve' class). When ANN2 was used to diagnose the remaining six classes, the 'heating curve class' was assumed to have been detected and readjusted. Both networks were multi-layered feed-forward networks with a tan-sigmoid transfer function and were trained with an improved back-propagation algorithm. Both were two-layer networks, i.e., one hidden layer and one output layer. Three parameters and the bias neuron were used as the inputs of ANN1. Two neurons were used in its hidden layer and two neurons were used as the output. Five parameters were used for coding the training patterns and the testing patterns, thus ANN2 has six input neurons. The output patterns of ANN2 decided six neurons to be in the output layer. Four hidden neurons were used in the hidden layer.

FDD Results

During training, ANN1 could detect the 'heating curve' mode from the other modes, but it was not able to detect the 'heating curve too low' on days with a strong solar influence. It classified 'boost heating too late' as 'heating curve too low' in a relatively high percentage (26%) of the cases. For the other training classes, the fault detection rate and the non-detection rate of ANN1 were no higher than 11%.

Table 2.11 Classification rates during testing

Actual Class	Classified in (%)						
	Normal	Bad combustion	Heat exchanger	Early boost	Late boost	Leaky valve	Not classified
Normal	88	0	0	3	6	0	3
Bad combustion	0	97	0	0	0	0	3
Heat exchanger	0	6	94	0	0	0	0
Early boost	9	0	0	91	0	0	0
Late boost	0	0	0	0	100	0	0
Leaky valve	0	0	0	0	0	91	9

The paper did not describe the severity of the faults simulated.

Li, X., V. Hossein, and J. Visier, 1996, "Development of a Fault Diagnosis Method for Heating Systems Using Neural Networks," *ASHRAE Transactions*, Vol. 102, Pt. 1, 607-614.

2.3.12 A Neural Network Prototype for Fault Detection and Diagnosis of Heating Systems

Authors: Xiaoming Li, Jean-Christophe Visier, and Hossein Vaezi-Nejad

Overview

An artificial neural network (ANN) prototype for fault detection and diagnosis (FDD) in complex heating systems was presented in this paper. The prototype was developed by using the simulation data of a reference heating system. The prototype was then generalized to four heating systems not used during the training phase. Six categories of fault modes and a reference normal mode were modeled and the results from two types of ANN structures were compared. The paper demonstrates the feasibility of using ANNs for detecting and diagnosing faults in heating systems, provided that there are available training data representative of the behavior of the systems with and without faults.

FDD Method

Before establishing the network, the main characteristics of the reference system were defined. The reference and six fault operating modes were modeled according to specific patterns under consideration. All the modes were simulated in five different heating systems for purposes of constructing a database. This database was used not only to develop the neural network structures, but also to test the generalization capability of the developed network structures.

Pertinent parameters were chosen carefully to construct the network inputs. The number of input neurons is equal to one bias neuron plus the number of the components that code the training patterns and the testing patterns in one specific representation space. The procedure to determine the number of neurons in a hidden layer consists of training different networks with increasing numbers of neurons. Then the sum-squared error (SSE) between the target outputs and the actual outputs of all the training patterns are computed. A compromise between the number of neurons and the SSE should be found. This study used as many neurons in the output layer as the number of the classes to be discriminated during the training phase. The ANN was then trained using commercial software with an improved back-propagation algorithm. The central idea in developing neutral network structures is as follows: use only the reference heating system to develop the best neural network structure and then test its generalization capability by applying it to the other systems not used during the training stage.

FDD Evaluation

The paper focused on the FDD of heating systems. The evaluation consisted of the following steps:

1. A database representing the different operating modes of a heating system with and without faults was established. The operating modes (six categories of fault modes and a reference normal mode) were modeled in five different heating systems.
2. Seven parameters were chosen and normalized to act as the inputs of the ANN.
3. Two types of network structures were proposed. This included the decision of how many neurons to use in the hidden and output layers, as well as the number of layers in the network.
4. The structures were trained using commercial software with an improved back-propagation algorithm. The data of the reference heating system were used in this stage.
5. The other four sets of data from different systems were used to test the generalization capability of the ANN.

The six fault modes and reference mode were placed within the following six classes:

1. Class 0 was the normal class, with no faults present.
2. Class 1 was the combustion class, denoting bad combustion in the burner.
3. Class 2 was the heat exchanger class, which includes the presence of scaling and dirt accumulation.
4. Class 3 was the heating curve class, when the heating curve was too low it meant that the supply hot water temperature was too low to maintain the indoor air temperature setpoint.
5. Class 4 had the early and late boost subclasses, which indicated a problem in when the boost heating was occurring.
6. Class 5 was the leaky valve class, which simulated leakage in a 3-way valve from the direct path into the bypass.

FDD Results

Although the ANN prototype was trained by only one simulated heating system, it showed good generalization capability (see table below). The two proposed network structures were trained, tested and compared. The single artificial neural network (SANN) performed better than the multiple artificial neural networks (MANN) probably because the single network structure can learn a global knowledge more easily than those composed of multiple networks.

Table 2.12 Classification rates from SANN

Tested class	Classified in (%)							
	Normal	Combustion	Exchanger	Heating curve	Early boost	Late boost	Leaky valve	Non-classification
Normal	91	0	0	0	6	0	0	3
Combustion	3	91	0	0	0	3	0	3
Exchanger	0	0	100	0	0	0	0	0
Heating curve	0	0	0	100	0	0	0	0
Early boost	3	0	0	0	91	0	0	6
Late boost	0	0	0	0	0	100	0	0
Leaky valve	6	0	0	0	0	0	94	0

So far, the FDD prototype has been studied only on simulation data. In addition, there is no information about the severity of the faults detected.

Li, X., J. Visier, and H. Vaezi-Nejad, 1997, "A Neural Network Prototype for Fault Detection and Diagnosis of Heating Systems," *ASHRAE Transactions*, Vol. 103, Pt. 1, pp. 634-644.

2.3.13 Fault Detection and Load Monitoring in Ventilation Systems

Authors: L.K. Norford, and R.D. Little

Overview

First, the paper classified faults for ventilating systems consisting of fans, ducts, dampers, heat exchangers, and controls. Next, the paper reviewed two forms of steady state parametric models for the electric power used by the ventilation system fans and then proposed a third model that corrected the power of a variable-speed-drive control signal. The models were then compared on the basis of their prediction accuracy, sensor requirements and ability to detect faults. Error analyses associated with model fits were also discussed. The uses of parametric models to distinguish between multiple fans from a single electric power measurement were also described.

FDD Method

The developed models compare the measured power with the predicted values to determine whether the power is normal or faulty. The first model discussed power as a quadratic function of environmental variables and control set points (thermal load and supply air temperature set point). The inclusion of the setpoint variable presented a difficulty in fault detection whenever the supply air temperature setpoint was adjusted. Measured fan power lags the setpoint change while the estimated fan power does not, thus leading to a false alarm. This problem can be eliminated if fan power is modeled as a function of airflow, which reflects the current dynamic conditions. Although fan power has been experimentally shown to correlate well with volumetric flow rate, there are significant deviations between measured and model prediction when the airflow is relatively low (during periods of increasing fan power). According to the paper, the difference was thought to be the result of changes in pressure within the throttling range of the pressure controller.

The author then proposed a third type of model. Since airflow data are not always available in HVAC control system, the author corrected the fan power with the fan motor speed control signal to provide a basis for fault detection without airflow data. The pressure deviations from setpoint at low airflow rates are not as apparent as when correcting power with airflow, because the fan shaft power varies weakly as a function of airflow for constant fan speed, particularly at higher airflow.

Based on the results of the fault detection evaluations for the three methods (listed in the next section), the author proposed using the correlation of the third method (the power vs. the fan speed control signal) in conjunction with a another correlation of the speed control signal with the same independent variables used by the first model to eliminate the need for electrical submetering. This approach requires two steps:

1. Establish, on a one-time basis—subject to periodic updates—the correlation between power and speed control signal.
2. Correlate motor speed control signal with environmental variables and such control setpoints as chilled-water temperature and supply air temperature.

FDD Evaluation

The paper considers four categories of faults in a variable air-volume (VAV) ventilation system, assigning several causes to each:

1. Failure to maintain supply air temperature setpoint. The causes include sensor error; malfunctions of chilled water valve or valve actuator; malfunctions of outdoor air damper, damper actuator, or economizer controller; and insufficient cooing capacity under high load conditions.
2. Failure to maintain supply air pressure setpoint. The causes include sensor error; malfunction of inlet vane, vane actuator, or motor speed controller; and insufficient fan capacity under high flow conditions.
3. Increased pressure drop. The causes include pressure changes upstream (or downstream) of the static pressure setpoint.
4. Malfunction of fan motor, coupling to fan, and fan controls. This category includes fan motors running at inappropriate times; and fan, fan motor bearing, belt and sheave problems.

The paper examined whether the independent variables specified in the three models could detect the types of faults listed. The paper did not describe in detail how the evaluation was performed; however, error analysis associated with model fits was thoroughly discussed.

FDD Results

The first type of model could detect the following fault modes: failure to maintain supply air temperature at the optimal value, pressure setpoint and pressure drop faults, and fan motor operation problems. It cannot isolate motor and coupling problems.

The second type of model could detect every failure mode except the one associated with supply air temperature.

The third type of model cannot detect the failure modes, except the one associated with fan motor problems.

The paper did not give evaluation results of the ‘conjunction’ model or provide a sensitivity analysis.

It was concluded that the correlation of electrical power with motor speed control signal contributes to industry objectives to reduce the instrumentation burden for fault detection and optimal control.

Norford, L.K. and R.D. Little, 1993, “Fault Detection and Load Monitoring in Ventilation Systems,” *ASHRAE Transactions*, Vol. 99, Pt. 1, pp. 590-602.

2.3.14 Optimal Control and Fault Detection in Heating, Ventilating, and Air-Conditioning Systems

Authors: F.L.F. Pape, J.W. Mitchell, and W.A. Beckman

Overview

An energy management and control system (EMCS) is employed in an HVAC system to collect data which are used to detect faults in system operation by comparing measured system power to predicted power according to the optimal control strategy. Various statistical approaches are used to differentiate between the actual and optimal power. Individual and trend measurements are used for the detection and diagnosing of faults.

FDD Method

The HVAC system has two control variables: the chilled-water setpoint and the supply air temperature. The total power is the sum of the chiller compressor, cooling tower, air-handler fans, and the chilled-water and condenser pumps. A control strategy is implemented to operate at the optimal (minimal) energy consumption rate.

Comparing the estimated power consumption with the actual consumption permits the determination of whether a fault is present.

Various methods were explored for their ability to detect faults. The first was the single-measurement approach. To detect a fault with this method the residual of the measured and predicted power value must lie outside the confidence interval.

The 'sequence of measurement' approach uses the sum of collected residuals to ascertain whether a fault has occurred based on the slope of the residual sum. Another method takes an average of a sequence of several data points, which is used to make a statistical comparison to normal operation.

Once a fault in the overall system is found, checking individual relations of each component's power consumption identifies the specific component where the fault occurred. Some faults may affect the power consumption of several components; therefore, a statistical analysis is performed on all the component's residuals.

FDD Evaluation

A computer model is developed of the chilled water plant and variable air volume air-conditioning system. Faults are introduced as errors in the actual setting of the chilled-water temperature and air supply temperature as compared to the optimal setting.

To determine if the model can locate a fault in the system, a positive error in the chilled-water temperature sensor was investigated. The physical effects would be lower chiller efficiency (requiring more chiller power) and lower pump power to maintain the air supply temperature because the chilled-water temperature is lower and a lower water flow rate is required.

FDD Results

For the single-measurement approach, the chilled-water sensor must be off by 4°F before many of the residuals are outside the 95% confidence interval.

In the fault location test where the chilled-water sensor had a positive error introduced, a clear increase is visible in the cumulative sum of the chiller power residual; moreover, the cumulative sum of pump power residuals decreases (each can be detected within 1°F errors in chilled-water temperature). The cumulative sum of fan power residuals indicates no trend and thus the supply air temperature measurement is unaffected.

Pape, F.L.F. and J.W. Mitchell, 1990, "Optimal Control and Fault Detection in Heating, Ventilating, and Air-Conditioning Systems," *ASHRAE Transactions*, Vol. 97, Pt. 1, pp. 729-736.

2.3.15 Typical Faults of Air-conditioning Systems and Fault Detection by ARX Model and Extended Kalman Filter

Authors: Harunori Yoshida, Tatsuhiro Iwami, Hideki Yuzawa, and Masami Suzuki

Overview

The authors describe, test, and analyze the effectiveness of two methods for finding abrupt faults. The first is an autoregressive exogenous (ARX) model and the second is based on an extended Kalman filter. The paper also summarizes a survey about typical faults that are commonly encountered in air-handling systems.

A questionnaire was prepared to collect information ranging from design faults to user-level faults. The consequences of a fault were classified into four cases as to whether they related to poor environment, energy consumption, reference or design value, or physical damage. Experts from the fields of design, fabricating and maintenance were asked to respond. The survey's results are listed in Table 2.13.

Table 2.13 Ten important faults selected by all professions

Rank	Process Variable Deviation	Affected Component
1	Poor air quality	Occupants
2	Water leakage	Piping
3	Room air temperature deviation	Occupants
4	Room air temperature deviation	Air diffuser
5	Too much or little air volume	VAV unit damper
6	Excessive pressure difference across an air filter	Air filter
7	Abnormal noise or vibration	Duct-work
8	Room air temperature deviation	Air diffuser
9	False opening signal to a VAV unit	Room air thermostat
10	Room air temperature deviation	Piping

The author did some analysis on the above chart:

- Many of the faults are at the stage of design or fabrication, making an FDD system preferable.
- It is important to make it clear for whom an FDD system is provided because different professions evaluate the importance of the faults differently.
- Pure mechanical faults or sophisticated operational faults can be hidden behind these trivial faults.

Furthermore, it was found from a study of the pure hardware faults that:

- A blocked air filter is the most common fault.
- Mechanical faults are widely seen.
- The number of faults in the category of 'difficult detection' is larger than that of all the others, suggesting that an FDD system should tackle these types of faults.

According to the survey, the author concluded the aims of an FDD system should be:

1. To promptly predict possible deterioration of materials or components.
2. To detect inefficient operation
3. To find faults that even an expert cannot detect.

FDD Method

The ARX model approach to fault detection uses the dynamic performance of the system including the controller using the following model:

$$y_n = -\sum_{i=1}^{n} a_{n-i} y_{n-i} + \sum_{j=0}^{q} b_j z_{n-j} + v_n$$

where:
y = model output
z = model input
v = random variables (normally distributed)
a = autoregressive parameters (order p)
b = exogenous parameters (order q)

The parameters (a and b) and the order of the model (p and q) are identified using a recursive least squares algorithm and the simulated variables y and z.

During the operation of the HVAC system, the parameters are identified and updated every sample time. The value 'S' follows a chi-squared distribution and can serve as the indicator of the presence of faults.

$$S = \sum_{k=n}^{n-L+1} (\hat{y}_k - y_k)^2$$

where L is the data window length for fault detection. The parameters of the ARX method do not have physical meaning, which restricts the method to fault detection.

The extended Kalman filter approach to fault detection starts by treating each component in the HVAC system as linear, thus the entire control loop can be considered linear. Therefore, the governing equation of the controller system can be known if the parameters of the controller component performance are known. By defining a new vector, the state space can be rewritten. The final equations are nonlinear and can be solved by applying the extended Kalman filter algorithm, which the paper did not describe. The model used in the extended Kalman filter method is based on the physical structure of the plant and therefore fault diagnosis is possible.

FDD Evaluation

A reference air-handling unit (AHU) system was used for fault simulation. The fault introduced into the variable air-volume (VAV) ventilation unit is a malfunction that causes the opening ratio to remain at the value just before the fault. The simulation was performed under cooling operations. Three typical days with different weather conditions, clear, half-cloudy, and cloudy, were simulated. The ARX model order was set at p=3 and q=7. The sampling interval was 2.5 minutes and the values of the window length were N=72 and L=8.

Two types of faults were simulated in the extended Kalman filter approach:

1. The actuator of the control valve of the AHU fails and the current valve position is subsequently locked.
2. The temperature sensor fails and the signal to the controller is subsequently locked.

The first test had a sampling time of 2.5 minutes and an evaluation interval of 15 minutes. The second test had a sampling time of 5 minutes and an evaluation interval of 30 minutes.

FDD Results

It was concluded that the ARX method performs well if the cooling load is not too small. The author did not present sensitivity data.

Tests showed that shorter sampling times were better for the extended Kalman filter method. The first test was able to detect the faults within 30 minutes. However, when the sampling time was lengthened to 5 minutes, the faults could not be detected.

Yoshida, H., T. Iwami, H. Yuzawa, and M. Suzuki, 1996, "Typical Faults of Air-Conditioning Systems and Fault Detection by ARX Model and Extended Kalman Filter," *ASHRAE Transactions*, Vol. 102, Pt. 1, pp. 557-564.

2.4 Generic Approaches

2.4.1 Reliability and Fault Diagnosis Methods of Power System Components

Authors: E. N. Dialynas, A. V. Machias, and J. L. Souflis

Overview

The paper describes the development of an expert system, which can diagnosis faults in power system components. An inference engine is based on knowledge acquired from component field outage data and Bayes' theorem. The expert system is demonstrated on power system transformers.

Component outages are divided into the following categories:

1. Permanent outages
2. Temporary outages

3. Transient outages
4. Scheduled maintenance outages

The various outages were categorized according to their failures and correlated to other information, including weather conditions.

The paper defines an expert system "as one that handles real world, complex problems requiring an expert's interpretation and solves them using a computer model of expert human reasoning." This paper uses an expert system called Failure Nature Classification, which consists of the following modules:

1. The knowledge base
2. The inference engine
3. The knowledge-acquisition module
4. The explanatory interface

The knowledge base contains three basic data formats:

1. The particular category of fault nature
2. The particular failure causes
3. The particular disconnection procedure

The expert system implements Bayes posterior probability method. The inference engine utilizes the rule value approach. The expert system classifies the failures of a power system transformer as mechanical, electrical, or magnetic.

No method results were presented.

Dialynas, E.N., A.V. Machias, and J.L. Souflis, 1987, "Reliability and Fault Diagnosis Methods of Power System Components." In S. Tzafestas, M. Singh, and G. Schmidt (Ed.), *System Fault Diagnostics, Reliability and Related Knowledge-Based Approaches* (Vol. 1, pp. 327-341). Dordrecht, Holland: D. Reidel Publishing Company.

2.4.2 An Expert System Design Using Cause-Effect Representations and Simulation for Fault Detection

Authors: A. H. Jones and S. E. Burge

Overview

A fault isolation diagnostic technique was developed by reasoning from first principles using knowledge about the system's structure and behavior. The resulting expert system was demonstrated for an air-brake fault-isolation system.

The central issues in developing an expert system were the representation and use of knowledge about causality, functionality, and physical dynamics of a system. Two different types of knowledge were used:

1. Shallow knowledge consists of inference rules which capture conclusions that can be made
2. Deep knowledge provides the lower level, casual, functional, and physical information in problem solving

Diagnostic problem solving was viewed as the interaction between simulation and inference, thus providing the following advantages:

- It allows systematic isolation of possible faulty devices
- It allows the system to deal with a wide range of faults, since the failures are defined functionally
- It allows a natural use of hierarchical descriptions which is advantageous for complex structures
- It allows the system to yield symptom information about the malfunction

The paper addresses the relevant concerns of an expert system, and uses the aforementioned interaction to develop a cause-effect network organized for shallow knowledge (the 'causal knowledge base') and a simulation network organized for deep knowledge (the 'simulation knowledge base').

Simulation generates expectations about the behavior of the functions. Inference generates conclusions about actual behavior based on observed outputs and device inference rules.

The causal knowledge base consists of a frame-oriented dictionary and a three-level semantic network. The dictionary determines entry points into the causal network. The semantic network models the reasoning process of the expert and known cause-effect relationships. The causal network is composed of three levels; the lowest is the 'information level', followed by the 'hypothesis level', and then the 'solution level'.

For the simulation knowledge base, the inclusion of all possibilities destroys the ability of the system to discriminate among potential candidates. Therefore, a hierarchy of models is proposed using the most restrictive first, and relying on the less restrictive models only when contradictions are encountered.

During the problem solving session, the system asks the user questions taken from a problem-solving dictionary in order to narrow the range of possibilities. It then runs a simulation to verify that the symptoms constitute a problem. Diagnostic rules isolate the most important symptoms, which are collected and prioritized. The causal knowledge base is searched to find the most likely fault to cause the observed symptoms.

A very brief example is given as to how the system would be applied to an air-braking system.

Jones, A.H. and S.E. Burge., 1987, "An Expert System Design Using Cause-Effect Representations and Simulation for Fault Detection." In S. Tzafestas, M. Singh, and G. Schmidt (Ed.), *System Fault Diagnostics, Reliability and Related Knowledge-Based Approaches* (Vol. 2, pp. 71-80). Dordrecht, Holland: D. Reidel Publishing Company.

2.4.3 A Look at the Knowledge-based Approach to System Fault Diagnosis and Supervisory Control

Author: Spyros G. Tzafestas

Overview

The paper presents the basic concepts and issues involved in knowledge-based expert systems by discussing some of the knowledge engineering tools available.

The components of expert systems are:

- A knowledge base containing facts, rules, heuristics and procedural knowledge
- An inference engine consisting of reasoning or problem solving techniques
- A user friendly interface

The expert systems used for fault diagnosis are divided into two categories:

1. Shallow reasoning approach is based on pre-specified relationships between fault symptoms and system malfunctions.
2. Deep knowledge approach is based on a structural and functional model of the problem domain. It attempts to predict the underlying principles of the domain; hence not every fault scenario needs to be found. Deep knowledge system methods are:
    a. 'Causal search method' traces process malfunctions to their source
    b. 'Mathematical model method' relies on redundancy between process measurements
    c. 'Hypothesis/test method' determines the symptoms of a postulated fault and compares the result to the process observables

The naive causal reasoning formulation combines shallow and deep reasoning to make explicit what is common to all causal reasoning. The diagnosis problem is stated such that "given a description of the causal structure of a technological process, and indications of whether the observable properties have normal value or not; find an explanation for the system behavior, either in terms of abnormal external causes or in terms of components, which, if they are malfunctioning, cause the process to behave as observed."

The ontological analysis approach follows the deep knowledge approach and analyzes the knowledge structures necessary to diagnosis a fault by checking the objects and relationships that occur within the fault diagnosis. The ontological structure can be divided into three levels:

1. Static ontology defines actual physical objects in the problem domain and their properties and relationships
2. Dynamic ontology defines the state space of the problem solving task and the actions that transform the problem from one state to another
3. Epistemic ontology defines the form of constraints and heuristics that control navigation of the state space

The attribute grammar approach allows the combination of factual and procedural knowledge in a single tool. A practical implementation of the approach states the problem as a series of logic rules, with each rule assigned a certainty measure.

The paper concludes with a discussion on using expert systems for on-line process supervision. The hierarchical functions of process management are:

- Direct interaction with the process; composed of data acquisition, event monitoring, and the direct control function
- Supervision function
- Executive production scheduling and operational management function

Tzafestas, S.G., 1987, "A Look at the Knowledge-Based Approach to System Fault Diagnosis and Supervisory Control." In S. Tzafestas, M. Singh, and G. Schmidt (Ed.), *System Fault Diagnostics, Reliability and Related Knowledge-Based Approaches* (Vol. 2, pp. 3-15). Dordrecht, Holland: D. Reidel Publishing Company.

3.0 FDD Survey Papers

3.1 Detecting Changes in Signals and Systems—A Survey

Author: Michèle Basseville

Overview

This paper is a survey of methods used to detect changes in signals and systems. An emphasis is placed on statistical (parametric) methods of detection.

Problems are classified according to:

1. Segmentation of signals and images for the purpose of recognition and monitoring
2. Failure detection in controlled systems
3. Updating the gains in adaptive algorithms, for tracking quick variations of the parameters

The first class of problems is demonstrated by an example of identifying continuous speech. The second is shown by an example of vibration monitoring of structures under natural excitation. The third class is represented by an example of failure detection in an air conditioning system.

Two tasks taken in solving these problems are:

1. Generating residuals (signals indicating change)
2. Design of decision rules based upon these residuals

Both deterministic and stochastic approaches have been used in solving these tasks; this paper focuses primarily on parametric statistical methods. The author specifically mentions using the likelihood ratio approach in solving problems directly without considering task 1 (assuming no constraints on algorithm complexity).

The primarily trade-offs identified are: mean time between false alarms and the delay of detection, and efficiency versus complexity.

The rest of the paper is devoted to the following topics: using the likelihood ratio test to detect a jump in the mean, detecting additive changes in linear systems, using a two-model approach to detect changes in spectral properties, presenting a general framework of the likelihood approach, using cumulative sum type algorithms in the statistical local approach, how to get around nuisance parameters, using deterministic and stochastic solutions to generating residuals, and concluding with problem diagnosis.

Basseville, M., 1988, “Detecting Changes in Signals and Systems—A Survey,” *Automatica*, Vol. 24, No. 3, pp. 309-326.

3.2 Fault Diagnosis in Dynamic Systems Via State Estimation--A Survey

Author: Paul M. Frank

Overview

A survey of methods for detecting and locating sensor and component faults using single, multiple, and hierarchical state estimation. These state estimators are either Luenberger (reduced order) observers or Kalman filters.

An alternative to hardware redundancy in failure detection is analytic redundancy, which requires a mathematical model of the system. Literature published to date (1987) is divided into two categories, parameter estimation methods and state (or output) estimation methods. The latter is the focus of this paper.

A brief review of literature on fault detection contains a progression of state estimation methods from 1971 to 1986.

A distinction is made between instrument failure detection (IFD) and component failure detection (CFD). Within these categories there are descriptions of different estimator schemes: the simplified observer scheme, the generalized observer scheme, and the hierarchical observer scheme (the upper level is called available-state coupled observer scheme and the lower level the estimated-state coupled observer scheme).

The strategies for evaluating the residuals of fault detection are threshold logic, additive decision functions, multiplicative decision functions, multiple hypothesis testing, and knowledge-based systems.

Several approaches to reducing the sensitivity of the parameter variations in fault detection are the robust observer scheme, the differential error observer scheme, the robust covariance matrix test, and an IFD scheme using unknown input observers.

Using state estimation for fault detection relies on the following idealized assumptions:

- Knowledge of the mathematical model of the process (structure and parameters)
- Knowledge of the characteristic of noise
- Observability of the system
- Preciseness of the solution of the analytical equations
- Linearization of the model and assumption of white noise (in many cases)
-

These methods are therefore easier to apply to electrical and mechanical systems than to thermodynamic and chemical processes.

An example of IFD using robust observer scheme in the primary circuit of a nuclear reactor in Karlsruhe, Germany is explained. This subsystem is 7^{th} order (7 state variables) and has 3 inputs and 5 outputs. There are 5 observers, each one driven by one of the outputs. A 2% failure of reactor thermal power registered as a 0.8°C estimation error, whereas a 10% change in the most sensitive parameter only resulted in a 0.1°C estimation error. Further examples are given for IFD in the steam generator in the nuclear reactor using the differential error observer scheme, and CFD in the primary circuit of the nuclear reactor using a local hierarchical observer scheme.

Another example included IFD of the turbo set of a boiling water reactor using the robust covariance matrix test. This system had 5 inputs, 4 states, and 4 measured output variables. The accompanying figure is not well documented.

Two more examples are given in some detail, a three-tank system and an inverted pendulum. Moreover, the appendix gives a large number of applications and the corresponding fault detection procedures that were implemented (very brief descriptions for each).

Frank, P.M., 1987, "Fault Diagnosis in Dynamic Systems via State Estimation: A Survey." In S. Tzafestas, M. Singh, and G. Schmidt (Ed.), *System Fault Diagnostics, Reliability and Related Knowledge-Based Approaches* (Vol. 1, pp. 35-98). Dordrecht, Holland: D. Reidel Publishing Company.

3.3 Fault Diagnosis in Dynamic Systems Using Analytical and Knowledge-based Redundancy--A Survey and Some New Results

Author: Paul M. Frank

Overview

The paper outlines the principles and techniques of model-based residual generation using parameter identification and state estimation. Emphasis is placed on the ability to achieve robust fault detection by decoupling the effects of the faults from one another. If decoupling is not possible, then approximate solutions are given in the time and frequency domains. The paper concludes with a basic scheme of fault diagnosis using a combination of analytical and knowledge-based redundancy.

The paper distinguishes between instrument fault detection (IFD), actuator fault detection (AFD), and component fault detection (CFD).

The formulation of the fault detection and isolation problem starts with system specification. The effects to model are:

- Faults in the actuators, components, or sensors
- Modeling errors between the actual system and its mathematical model
- System noise and measurement noise

Fault modes may be abrupt or incipient (slowly developing). Abrupt faults typically are safety issues, whereas incipient faults are relevant to maintenance issues.

To be able to detect and distinguish a fault, the following conditions must hold:

- Knowledge of the normal behavior
- Definitiveness of the faulty behavior
- Existence of analytical redundancy relations
- Availability of at least one observation reflecting the fault
- Satisfactory reliability of redundant information

The methods of residual generation can be categorized using the following basic concepts:

1. The parity (consistency) space approach (checks consistency of mathematical equations of the system using the actual measurements).

2. The dedicated observer approach and innovation-based approach (attempt to reconstruct the outputs from the measurements using observers or Kalman filters).
3. The fault detection filter (fault sensitive filter) approach (a full-order state estimator with a special feedback gain matrix).
4. The parameter identification approach (takes advantage of the fact that faults manifest themselves in various physical parameters; faults are detected by estimating the parameters).

The author discusses the generation of robustness in the parameter estimation and state estimation approaches. Using unknown input observers to develop robust residual generation is superior to the detection filter approach because it accounts for modeling errors, and to the parity space approach since it takes into account the sensitivity to the faults.

Optimal time domain and frequency domain approximations are given.

The general structures for IFD, CFD, and AFD are given along with their corresponding optimal robust observer schemes based on the number of faults to be detected at the same time.

The paper concludes with a brief discussion of knowledge-based models. Such a fault detection system should consist of the following components:

1. The knowledge base (knowledge of facts and rules)
2. The data base (information about the process' present state)
3. The inference engine, which has access to:
    a. The analytical knowledge in terms of the mathematical model (structure and parameters)
    b. Heuristic knowledge of fault propagation, fault statistics, operational and environmental conditions, process history, etc.
    c. The actual data (inputs, outputs, operating conditions, etc.)
4. The explanation component (to inform the user on why and how the conclusions were drawn)

Frank, P.M., 1990, "Fault Diagnosis in Dynamic Systems Using Analytical and Knowledge-Based Redundancy – A Survey and Some New Results," *Automatica*, Vol. 26, No. 3, pp. 459-474.

3.4 Survey of Model-Based Failure Detection and Isolation in Complex Plants

Author: Janos J. Gertler

Overview

The main features of model-based failure detection and isolation methods have been surveyed in this paper.

The author proposed that failure detection and diagnostics consist of three major tasks: failure detection, isolation and identification. The first two were regarded as absolute musts in practical systems and the latter one would require considerable work in numerical estimates that may not be worth the effort.

The author classified the faults considered into three classes:

1. Additive measurement faults, which are discrepancies between the measured and true values of plant input or output variables (e.g., sensor biases and actuator malfunctions)
2. Additive process faults, which are disturbances acting on the plant (e.g., plant leaks and loads)
3. Multiplicative process faults, which are changes of the plant parameters (e.g., deterioration of plant equipment)

The model-free approaches to fault detection and isolation were only briefly reviewed and classified into the following groups: limit checking, installation of special sensors, installation of multiple sensors, frequency analysis of plant measurements, and expert system approach.

The general structure of model-based methods was analyzed. The stages of model-based failure detection and isolation are residual generation, statistical testing and logical analysis. The relationships among them are presented in Figure 3.1.

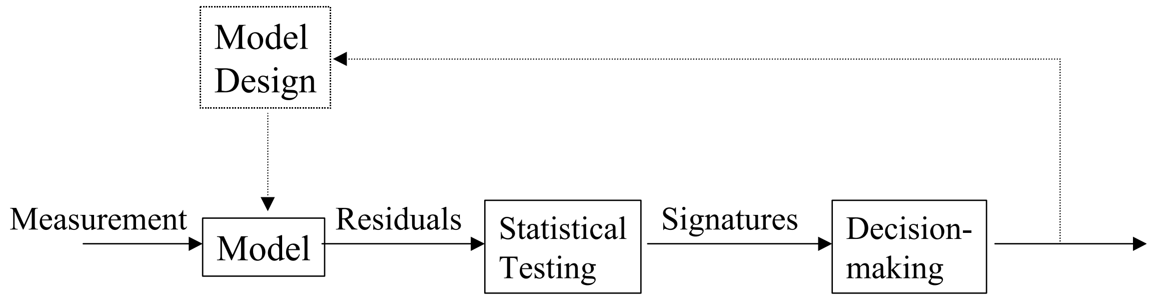

Figure 3.1 Stages of model-based failure detection and isolation

Most model-based failure detection and isolation methods rely on linear discrete time models. So any nonlinearity is linearized and continuity is discretized. The author presented the plant, failure models and the three types of faults within the general terms of control engineering.

Isolability, sensitivity, and robustness are quality properties of any failure isolation procedure that strongly influence the usefulness of such procedures. Careful selection and/or transformation of the plant model can influence these qualities. Isolability is the ability of a procedure to distinguish certain faults. Sensitivity is a qualitative measure characterizing the size of the faults that can be isolated. Robustness is the ability of the procedure to isolate faults in the presence of modeling errors.

The various approaches to generating residuals are:

- Straight input-output residuals. The residuals are defined as the product of the model matrix and the measurement vector.
- State-related residuals. The residuals are defined in terms of the output. If the residual is defined as the difference between the measured output and an estimate obtained by Kalman filtering, it is called an innovation. In other systems parallel observers are used. The state vector (or part of it) is estimated via two observers based on different (although possibly overlapping) sets of outputs, and the residual is defined as the difference between the two estimates. Finally, in distributed systems where the plant variables depend not only on time but also on the spatial position, the variables may be decomposed using time- and space-dependent factors.
- Identification-based methods. A residual-like quantity is defined in relation to the plant parameters. The plant is identified in a fault-free reference situation, then repeatedly on-line. The results of the latter are compared to the reference values and a parameter error (residual) is formed.

The approaches to statistical testing are:

- Direct parallel testing. Following each computation of the residuals, a separate test is applied to each element of the residual vector. Based on the tests, a Boolean signature vector is formed so that the element 'i' is 1 if the corresponding element in the residual vector fires the test. The advantage of this approach is that it is easy to administer and yields a distinctive binary signature. The disadvantage is that it does not utilize the additional information represented by the off-diagonal elements of the covariance matrix of the residuals.
- Multivariate testing. In the multi-dimensional space of the residuals, any constant probability density is described by a closed hypersurface. Selecting a level of confidence implies choosing one such surface. If the point defined by the residual is outside the limit surface, the system is declared faulty. This approach is difficult when administering the test to higher-dimensional residual vectors and it provides only a faulty/not faulty decision that does not facilitate the isolation of the failure.
- Compound scalar testing. A single scalar statistic is introduced as the product of the residual vector and the inverse of the covariance matrix. The scalar statistic follows the chi-square distribution with the same number of residuals as degrees of freedom. This method is easy to administer, but provides only binary inference.

- Sequential likelihood ratio test. The test compares the hypothesis of nonzero residual mean to the null hypothesis of zero mean. The decision is based on the likelihood ratio of the probabilities of the observed time series under the two hypotheses.
- Bayesian approach. This approach utilizes an *a priori* probability distribution of the occurrence of a set of failures. Such *a priori* distribution may be obtained from the observation of an extended history of the plant or may be assumed as design parameters.

The author pointed out that the isolability lies primarily in the structure of the model used in residual generation and, to a lesser degree, in the statistical test applied. The concepts of deterministic (zero-threshold) and statistical (high-threshold) isolability were discussed. To satisfy the conditions of deterministic isolability, a model transformation may be performed to attain the desired structure. Model transformation may be looked on as a reshuffling of zeros in the parity equations. The desired model matrix is specified in terms of its incidence matrix. Each zero in the incidence matrix determines a linear algebraic equation; the solution of these yields the elements of the transforming matrix. Another approach to model generation/transformation is to derive linearly independent sets of input-output parity equations first. Further parity equations are then generated as linear combinations of elements from a basic set.

Several topics about sensitivity and robustness were discussed. The marginal value of a fault that triggers the statistical test might be set as the measure of sensitivity. The author pointed out that failure sensitivity could be improved by filtering the residuals. A simple first-order filter was presented as an example. The main idea of the filter is that the fault-free variance of the residuals is designed to be much smaller than that of the residuals being analyzed. This type of filter works well if the residual equations are static or, in the case of dynamic equations, if the residuals depend on the faults in a proportional fashion. Otherwise, failure sensitivity might be reduced. The author also pointed out that robustness of the failure detection and isolation algorithm can be improved by desensitizing residuals with respect to certain modeling errors, which might by achieved by explicit algebraic cancellation of some terms in the residual equations.

Gertler, J.J., 1988, "Survey of Model-Based Failure Detection and Isolation in Complex Plants," *IEEE Control Systems Magazine*, Vol. 8, No. 6, pp. 3-11.

3.5 Process Fault Detection Based on Modeling Estimation Methods--A Survey

Author: Rolf Isermann

Overview

The paper provides a brief summary of some basic fault detection methods. A description of suitable parameter estimation methods for continuous-time models is also presented. Two examples are considered: the fault detection of a centrifugal pump by parameter monitoring and leak detection for pipelines by a correlation method.

Methods for fault collection can be based on the following quantities:

- Measurable signals
- Nonmeasurable state variables (can be estimated using measurable signals)
- Nonmeasurable process parameters (requires theoretical modeling of the system to determine effect of physical processes)
- Nonmeasurable characteristic quantities (is calculated using measured signals, such as efficiency)

The general structure of process fault detection requires a model of the normal process, a model of the observed process, and models of the faulty process.

To detect certain faults the following may be used:

- State estimation methods
- Parameter estimation methods
- Calculation of characteristic equations

Comparing these nonmeasurable quantities of the observed model with the normal model results in error signals or residuals. These changes are compared to fault models to determine whether a fault has occurred.

The first example's goal was to detect faults in a D.C. motor, centrifugal pump, and circulation system based on theoretically derived process models and parameter estimation. Using dynamic models allows more process coefficients to be monitored. A 7% increase in the armature resistance of a 4kW motor was detectable using the estimation techniques developed. Furthermore, the tightening and loosening of screws on the pump packing box was also detectable in the friction coefficient estimate.

The second example was the detection and localization of leaks in liquid and gas pipelines. A pipeline approximately 67 km long with a diameter of 0.273 meters was used to test the model. A leak was generated at a distance of 35.8 km with a mean leakage rate of 0.19%. The model's trigger level was exceeded 98 seconds after the occurrence of the leak and the leak location was estimated to within ±0.7% (500 meters) only 90 seconds after the alarm was triggered by the leak detection. Detection of gas leaks requires at least a 2% or higher leak rate and takes a minimum of several hours to detect.

Faults detection methods must be sensitive to the appearance of faults but insensitive to other changes, hence the following tradeoffs exist:
1. Size of fault vs. detection time
2. Speed of fault appearance vs. detection time
3. Speed of fault appearance vs. process response time
4. Size and speed of fault vs. speed of process parameter changes
5. Detection time vs. false alarm rate

Therefore, systems designed for the detection of abrupt faults may not be well suited for slowly developing faults.

Isermann, R., 1984, "Process Fault Detection Based on Modeling and Estimation – A Survey," *Automatica*, Vol. 20, No. 4, pp. 387-404.

3.6 Review of Laboratory and Field Methods to Measure Fan, Pump, and Chiller Performance

Authors: John Phelan, Michael Brandemuehl, and Moncef Krarti

Overview

The paper presents a comparison between measuring fan, pump, and chiller performance in a laboratory setting and in the field. The measurement method was evaluated by:
- Analyzing the data required for performance assessment
- The nature of the models in which the test data were used
- The physical engineering considerations to determine what to measure, how to measure it, and under what operating conditions

The paper describes the literature review of previous methods and an overview of methods developed in ASHRAE Research Project 827. This project's purpose "was to develop methods for in-situ testing of chillers, fans, and pumps in order to evaluate actions to improve efficiency of electric-powered HVAC equipment."

A table of equipment test standards was presented for chillers, fans, pumps, and motors. Moreover, an additional table of measurement standards for temperature, pressure, airflow, liquid flow, power, thermal meters, and systems was also provided.

The accuracy of measurements is covered in ASHRAE Standard 114. Some authors have demonstrated that to calculate a chiller efficiency within 3%, the flow meters must be accurate to 1% and the temperature sensors to 0.05°F.

The testing guidelines within ASHRAE RP-827 specified the following test characteristics:

- Physical characteristics to be measured
- Number of data points required
- Accuracy of measurements
- Reference to existing applicable measurement standards
- Methods of artificial loading
- Calculation equations and uncertainty analysis

Phelan, J., M. Brandemuehl, and M. Krarti, 1997, "Review of Laboratory and Field Methods to Measure Fan, Pump, and Chiller Performance," *ASHRAE Transactions*, Vol. 103, Pt. 2, pp. 914-925.

3.7 A Survey of Design Methods for Failure Detection in Dynamic Systems

Author: Alan S. Willsky

Overview

The paper surveys methods for detecting abrupt changes in dynamic systems. A general discussion on fault detection fundamentals and tradeoffs leads into different sections each highlighting a particular method.

Failure sensitive filters remain reactive to new data. Utilizing such filters has a drawback with increased susceptibility to sensor noise.

The use of voting techniques in parallel redundant systems can be used with simple logic. Otherwise, a set of recursive filter equations can be used to create a 'soft' voting procedure. Voting cannot be used to detect failures that affect both instruments in the same way.

Multiple hypothesis filter-detectors use a 'bank' of linear filters based on different hypotheses concerning the underlying system behavior. Some of the notable methods include the sequential probability ratio test (SPRT) and a Bayesian approach where an estimate is generated of the *a posteriori* probability that a given measurement is false.

Jump process formulations model potential failures as jumps, characterized by *a priori* distributions that reflect initial information concerning failure rates.

Innovations-based detection systems involve monitoring innovations of a filter based on the hypothesis of normal system operation. The normal filter is used until the innovations monitoring system detects some aberrant behavior. A generalized likelihood ratio (GLR) approach attempts to isolate different failures by using knowledge of the different effects such failures have on the system innovations.

These methods have been applied to systems in the aerospace industry and to the detection of electrocardiogram arrhythmias. A total of 65 papers are reviewed, with the most emphasis placed on the GLR approach.

The important issues in comparing failure detection methods are:

- Types of failure modes that can be considered
- Complexity in implementation
- Performance, as measured by false alarms, delays in detection, etc.
- Robustness in the presence of modeling errors

Willsky, A.S., 1976, "A Survey of Design Methods for Failure Detection in Dynamic Systems," *Automatica*, Vol. 12, pp. 601-611.

4.0 FDD Related Papers

4.1 Chiller Applications

4.1.1 Challenges in Modeling Vapor-Compression Liquid Chillers

Authors: Matthew W. Browne and Pradeep K. Bansal

Overview

The authors reviewed over 60 research papers on steady state and transient models of vapor-compression chillers, and discovered areas that still require investigation. They also stress the need for a 'complete' chiller model that incorporates detailed models of each component in the system.

The component models for a refrigeration system should include mass, momentum, energy-balance, thermophysical property data, heat transfer and work relationships.

The majority of models have been developed for steady-state operation and for small systems. Recent work has been done on steady state operation of chillers, but none exists for transient performance.

The compressor—which is usually screw, centrifugal, or reciprocating—is modeled as a steady state process because the dynamics are negligible. Polytropic compression is generally assumed, along with constant motor speed.

The heat exchangers are what set chillers apart from smaller refrigeration equipment. Most use shell-and-tube configurations with refrigerant in the shell and water passing through the tubes, often in multiple passes. The commonly used methods are NTU effectiveness and LMTD (Log Mean Temperature Difference). A more accurate method would be control volume analysis on small elements; however, this has not yet been done for chillers. Although correlations for heat transfer coefficients and pressure drops are available, they are not usually incorporated into the heat exchanger model.

The expansion valve is universally modeled as an isenthalpic process.

In steady state simulations, mathematical iteration is performed on the algebraic equations to reach a solution at the desired tolerance. Newton-Raphson is a well-known iterative solution technique used to perform this analysis.

Dynamic simulations require the solution of ordinary differential equations using numerical solution techniques. The Euler and Runge-Kutta methods are commonly employed. The finite difference method is used to solve the problem during the progression of time in space.

The need for a 'global approach' which links together detailed component models to develop a complete simulation model of a vapor-compression chiller is evident based on the lack of papers published in this area. This is necessary both for steady state and transient situations, of which there is no published literature of the latter.

The approach used in developing a complete model should incorporate the following ideas:

- Use accurate and specific heat transfer correlations for tube bank geometries
- Consider pressure drops on the refrigerant side
- Include relevant physical phenomenon in the compressor model, such as heat loss
- Be able to simulate part-load or off-design operation

Browne, M.W. and P.K. Bansal, 1998, "Challenges in Modeling Vapor-Compression Liquid Chillers," *ASHRAE Transactions*, Vol. 104, Pt. 1a, pp. 474-486.

4.1.2 On-site Chiller Testing

Authors: Swiki Anderson and Joseph C. Dieckert

Overview

The authors run a business that specializes in identifying chiller faults on-site and can subsequently implement the necessary corrective actions. They were experiencing difficulties in accurate diagnosis of the chiller faults and decided to develop a new method. The previous method relied on manual collection of data.

The newly proposed method utilizes a computer to collect all sensor measurements simultaneously. The goal was to take measurements, analyze the data, and evaluate and diagnose the chiller's performance without modifying its controls.

The instrumentation used to collect the data was only required to be precise in order to ensure repeatability of results. These instruments were also designed so that they could be recovered after the completion of testing without shutting the chiller off. A small, integrated temperature transmitter was attached to a 1/8-inch stainless steel probe. A dual rotor insertion meter was selected to measure water flow rates via a 'wet tap'.

The measured data included: compressor power input, condenser water flow rate, condenser water entering temperature, condenser water leaving temperature, chilled water flow rate, chilled water entering temperature, and chilled water leaving temperature.

According to ARI/ASHRAE 550, if the electrical energy input and heat removed from the chilled water equals the heat rejected to the condenser water to within ± 5% at steady state, then the data are reliable. The field tests performed thus far have given energy balances around ± 1% to ± 3%. When collecting data, the computer takes 25 data snap shots and then checks for stability. Additional data are collected until the last 25 readings reach acceptable limits.

"By using computers and accurate instrumentation, on-site chiller testing has changed from an expensive 'guessing game' into a reliable and useful tool for lowering operating and maintenance costs. Specific machine problems have been identified in the field by measuring and recording temperatures. This methodology has provided some diagnostic and tune-up capability to prudent users."

Anderson, S.A. and Joseph C. Dieckert, 1990, "On-site chiller testing," *ASHRAE Journal*, Vol. 32, April, pp. 54-60.

4.1.3 Optimum Chiller Loading

Author: Stephen B. Austin

Overview

Traditionally it has been assumed that optimum chiller loading is between 60%-80% for centrifugal chillers. However, the author intends to demonstrate that increasing the chiller load to a range of 80%-100% is better than operating two chillers at 40% load.

Optimum chiller load depends on the combination of compressor, drive motor, evaporator and condenser. Moreover, the condition under which a chiller is rated is also important. Chillers rated by ARI's standard use a varying condenser water temperature for part-load conditions. This overstates their efficiency for part-load conditions when the condenser water temperature is constant. For example, at 60% load the ARI condenser water entering temperature is 75°F; however, if the entering temperature is held constant at 85°F then the kW per ton efficiency value can be 15% higher than the ARI rating.

Data collected from an actual industrial facility showed that the condenser water temperature was higher at all loads than the ARI testing conditions.

Using the percent full-load amps to the compressor over-predicts the actual percent refrigeration load. At 60% full-load amps the refrigeration load is 55% and at 30% full-load amps the refrigeration load is only 20%.

The author recommends that the lead chiller be driven to 100% load before the lag chiller is brought on-line.

Austin, S.B., 1991, "Optimum Chiller Loading," *ASHRAE Journal*, Vol. 33, July, pp. 40-43.

4.1.4 Beware of Condenser Fouling

Author: Brad Buecker

Overview

The author studied the effects of fouling in a condenser, specifically a water-cooled steam-surface condenser located at the exhaust of a turbine. On the water side, the most common causes of condenser inefficiency are microbiological growth and scale formation.

The condenser's terminal temperature difference (TTD) is the difference between the temperature of the condensing steam and that of the circulating water at its outlet. Microbiological fouling is detected by a rise in the TTD. Injecting chemicals into the water is the normal preventative measure.

Frequently seen in recirculating systems, scaling occurs when the solubility of certain compounds in water decreases as the water temperature increases in the condenser. Scaling is harder to remove than microbe fouling, but the effects are similar. A custom preventative chemical measure must be adopted for each site as it is warranted.

Buecker, B., 1995, "Beware of Condenser Fouling," *Chemical Engineering*, Vol. 102, April, pp. 108-112.

4.1.5 Variable Flow—The Quest for System Energy Efficiency

Author: Donald Eppelheimer

Overview

Varying condenser water flow has long been used as a method of controlling head pressure in water-cooled refrigeration systems. This paper describes how the evaporator water flow can be controlled to improve energy efficiency. The paper deals exclusively with plants using multiple chillers in parallel.

Centrifugal chillers have automatic safety shut-offs which activate when unfavorable conditions are encountered on the power supply, motor amperage, oil pressure, and condensing pressure. Furthermore, the temperature control on centrifugal chillers is deliberately slow to prevent the chiller from overcontrolling. However, the refrigerant temperature immediately responds when the evaporator flow is varied, thus possibly causing the evaporator limit to trigger. A microelectronic control usually will average readings over a period of time to allow the chiller to respond by decreasing capacity.

Stability in the evaporator flow is much more important than in the condenser, because the chilled water flow impacts other systems, whereas the leaving cooling water does not influence any systems.

Eppelheimer, D.M., 1996, "Variable Flow—The Quest for System Energy Efficiency," *ASHRAE Transactions*, Vol. 102, Pt. 2. pp. 673-678.

4.1.6 Predictive and Diagnostic Aspects of a Universal Thermodynamic Model for Chillers

Authors: J.M. Gordon and Kim Choon Ng

Overview

A simple thermodynamic model was developed to capture the universal aspects of chiller behavior. The model predicts chiller performance over many different operating conditions by using just a few measurements. The model was tested with reciprocating, centrifugal, and absorption chillers; moreover, the universal aspects were illustrated with thermoacoustic and thermoelectric chillers. The term 'chillers' used here refers to any cooling and refrigeration device regardless of application.

Chiller performance can be characterized by curves of COP^{-1} against $(\text{Cooling Rate})^{-1}$. At lower cooling rates the dominant losses occur from fluid friction, throttling, de-superheating in the condenser, and heat leaks. At higher cooling rates the dominant factor is finite-rate heat transfer. Consequently, a maximum COP occurs when these losses are at a minimum. The irreversibility associated with finite-rate heat transfer is still a significant portion of all the losses at lower cooling rates; however, it contributes little to the dependence of COP on the cooling rate (since it does not vary much). Most reported chiller data occurs within the linear region of the chiller performance curve (lower cooling rates where the finite-rate heat transfer effect is nearly static).

The model of Gordon and Ng (1995) was derived from a simple first and second law analysis using empirical relations for the irreversibilities associated with the heat exchangers. For a given chiller, COP is correlated using the following form.

$$\frac{1}{COP} = -1 + \frac{T_c^{in}}{T_e^{out}} + \frac{-a_0 + a_1 T_c^{in} - a_2 \dfrac{T_c^{in}}{T_e^{out}}}{\dot{Q}_e} \qquad (1)$$

where T_c^{in} is the temperature of the secondary working fluid (air or water) entering the condenser, T_e^{out} is the temperature of the secondary working fluid leaving the evaporator (air, water, or water/glycol), $\dot{Q}_e$ is the rate of heat addition to the evaporator (cooling load), and a_0, a_1, and a_2 are empirical constants. The constants are determined using linear regression applied to a set of training data obtained from the equipment manufacturer, from laboratory tests, or from the field when the unit is operating normally. There are some advantages in using this model as compared with polynomial correlations that are typically employed. In particular, less data are required to obtain an acceptable fit and there is better confidence that the model extrapolates well to operating conditions outside of the range used to obtain the correlations.

The commercial chiller measurements were collected from units ranging in sizes of 1.4 tons to 1660 tons (3.516 kW equals one ton).

The centrifugal chiller was used to highlight the diagnostic capability of the model. Measurements were made of a centrifugal chiller over a 6-month period, in the middle of which the heat exchanger tubes were cleaned during a routine maintenance check.

The absorption chiller model required additional terms to account for the generator and absorber. Measurements were from a 2-ton commercial LiBr-water absorption chiller.

For the reciprocating chiller, from operating ranges of T_c^{in} =23.9°C to 53.0°C (75°F to 127°F) and T_e^{out} =4.4°C to 15.0°C (40°F to 59°F), the RMS error of predicted COP for 30 different chillers was 0.4%. This is much less than the ±3% experimental uncertainty of the measurements.

For the centrifugal chiller, there is a clear distinction between measurements made before and after the heat exchanger was cleaned. The COP increased by an average of 36% and the ordinate intercept of COP^{-1} was noticeably lower. Moreover, the plot of COP^{-1} against Q_e^{-1} remained linear with identical slopes despite the shift in the intercept.

The absorption chiller model predicted chiller COP within an RMS error of 3.85%, which is less than the experimental uncertainty of ±6.2%.

The performance curve of a thermoacoustic or thermoelectric refrigerator is consistent with the thermodynamic model developed for other cooling devices.

Gordon, J.M., and K.C. Ng, 1995, "Predictive and diagnostic aspects of a universal thermodynamic model for chillers," *International Journal of Heat and Mass Transfer*, Vol. 38, No. 5, pp. 807-818.

4.1.7 Design Issues of Variable Chilled-Water Flow Through Chillers

Author: Thomas Hartman

Overview

Many chiller systems run constant flow through the chiller and vary the flow through the load. Excess supply is bypassed back into the chiller with these systems (commonly through a decoupler pipe). There is an energy efficiency penalty associated with mixing bypassed chilled water and return water. Therefore, the author argues that only a single variable flow supply circuit be used. The paper discusses the advantages and problems associated with such a system.

One of the main concerns is controlling the chiller load with varying flow rates. The two must therefore be correlated together. One approach is coordinated chiller and pump (CCP) control. In CCP both the chiller and pump react to changes in the load. The chiller capacity is adjusted in proportion to the chilled-water pump power (or the cube of the pump speed). At 93% design water flow, the chiller operates at 80% (0.93^3) of maximum electrical demand.

Hartman, T.B., 1996, "Design Issues of Variable Chilled-Water Flow Through Chillers," *ASHRAE Transactions*, Vol. 102, Pt. 2. pp. 679-683.

4.1.8 New Techniques for Monitoring Condenser Flow Rate, Fouling

Authors: P. A. March and C. W. Almquist

Overview

A differential pressure measuring device is used to measure the change in pressure from the outlet waterbox to the outlet pipe. The outlet waterbox is the portion of the condenser where the water flow from the tubes is recombined. Measurements using this technique were shown to be far superior to the traditional method of measuring the change in pressure across the inlet and outlet of the condenser. The reason is that this measurement doesn't change much, because as fouling increases and resistance increases the flow rate tends to decrease.

A measurement called the DP ratio (not clear how it was calculated) steadily increased from 7 to 10 over the course of 90 days. After cleaning, the DP ratio returned to 7 and then moved back to 10 during the next 90-day period.

March, P.A. and C.W. Almquist, 1989, "New techniques for monitoring condenser flow rate, fouling," *Power*, Vol. 133, March, pp. 73-76.

4.1.9 Effect of Variable Flow on Centrifugal Chiller Performance

Author: George Redden

Overview

The effect of varying the chilled water and condenser water flow on centrifugal chiller efficiency was studied utilizing three different methods:

1. Theoretical heat transfer equations were examined to assess the effect on heat transfer
2. Chiller computer modeling for a packaged system was done to analyze a variety of flow and load conditions
3. A chiller was run on an ARI-certified test stand under varying conditions to correlate the results with the computer modeling

Evaporator performance became unstable for tube flow velocity under 2 ft/s, whereas condenser performance was normal for velocities as low as 1 ft/s. There was no significant difference in COP between evaporator flows at full load or at a reduced flow equal to the percent reduction in load.

Decreasing the water flow results in a decrease in tube velocity and hence a lower heat transfer rate. The evaporating temperature decreases slightly under constant load conditions, thus increasing the compressor head and reducing efficiency a small amount. On the other hand, lower water flow also increases the chilled-water temperature range, consequently improving the heat transfer rate.

In the computer simulation, 250-ton chillers were used in the testing with evaporator approach temperatures of 1°F, 3°F, and 7°F (the difference in temperature from the leaving chilled-water temperature and the saturated evaporator temperature). The entering condenser water temperature was 80°F. Chilled water entering temperature was 54°F and leaving temperature was 44°F at full load. For tests at 75%, 50%, and 25%; the evaporator flow rate was reduced proportionally to maintain the chilled water temperature range (the design full-load flow was also run for comparison).

A 225-ton centrifugal chiller on an ARI-certified test stand was used to verify the computer results.

Table 4.1 Selected test results

% of full load	Chilled water flow rate (gpm)	kW per ton	COP
100	540	0.586	6.0
71	540	0.613	5.7
71	400	0.606	5.8

During the 25% load test, a reduced flow of 130 gpm was used. This resulted in a tube velocity of 1.15 ft/s and temperature control of the leaving chilled water was unstable; however, using the design full-load water flow rate was still possible at 25% load.

Another set of tests run on a 250-ton chiller to study varying condenser water flow rates showed that operation remained stable (with a slight decrease in performance) even when the tube velocities were reduced to 0.4 ft/s.

The computer results were consistent with the laboratory testing.

Redden, G.H., 1996, "Effect of Variable Flow on Centrifugal Chiller Performance," *ASHRAE Transactions*, Vol. 102, Pt. 2. pp. 684-687.

4.2 Packaged Air-Conditioning and Refrigeration Equipment Applications

4.2.1 Common Faults and their Impacts for Rooftop Air Conditioners

Authors: Mark S. Breuker and James E. Braun

Overview

This paper identifies the most important faults to include in an automated FDD system. It also presents fault-free and faulty data that could be used to evaluate and optimize the performance of FDD methods.

A database of service records was analyzed from an HVAC service company. The faults were analyzed in terms of both frequency of occurrence and total cost of repairs. The causes that led to compressor failures were analyzed through interactions with industry personnel.

Transient operation of a rooftop air conditioner was simulated in the laboratory. A three-ton packaged rooftop unit—which has a constant speed, hermetically sealed, reciprocating compressor with on/off control and uses fixed-orifice type expansion devices for refrigerant flow control—was used for experimental testing.

Table 4.2 Simulated faults

Fault	Fault Implementation
Condenser fouling	Blocking the condenser coil with uniformly spaced, vertical strips of paper
Evaporator fouling	Reducing the speed of a variable speed fan used within an air flow measurement system
Liquid line restriction	Partially closing a globe valve placed in the liquid line
Compressor valve leakage	Using a bypass valve that allows gas from the discharge line to recycle into the suction line
Refrigerant leakage	Discharging a fixed amount of refrigerant from the unit into a receiving vessel

Fault levels, load levels, and ambient conditions were all varied during testing and a large database of measurements was generated. A total of 96 transient tests were performed.

The following measurements were taken in order to characterize the fault impacts (consult Figure 4.1):

1. T_{amb} is the temperature of the ambient air into the condenser coil
2. T_{ra} is the temperature of the return air into the evaporator coil
3. Φ_{ra} is the relative humidity of the return air into the evaporator coil
4. T_{wb} is the wet-bulb temperature of the return air into the evaporator coil
5. T_{evap} is the evaporating temperature
6. T_{sh} is the suction line superheat
7. T_{cond} is the condensing temperature
8. T_{sc} is the liquid line subcooling
9. T_{hg} is the hot gas line or compressor outlet temperature
10. ΔT_{ca} is the air temperature rise across the condenser
11. ΔT_{ea} is the air temperature rise across the evaporator

Air-side temperatures were measured with 1000Ω Platinum RTDs (accurate within 1Ω, or 0.26°C). Temperatures in the vapor compressor cycle were measured using K-type thermocouples (accurate within ± 0.5°C). Relative humidity was measured using a duct-mounted capacitive polymer humidity sensor (accurate within ±3% relative humidity).

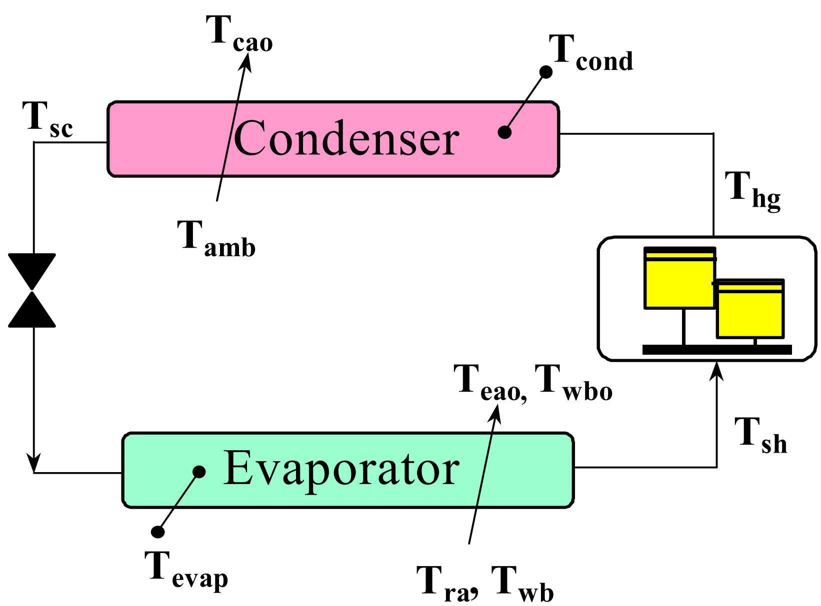

Figure 4.1 Temperature measurement locations

Transient tests were performed in environmental chambers that can simulate indoor and outdoor conditions. Four distinct load/ambient conditions were used for the transient tests (20%, 40%, 60%, and 80% of the air-conditioning unit's total cooling capacity). Furthermore, at each of the building load levels, faults were introduced into the test unit at four to five distinct levels as indicated in Table 4.3 Fault levels.

Table 4.3 Fault levels

Fault	Fault Level, %
Refrigerant leakage (% reduction in mass of charge)	0, 3.5, 7, 10.5, 14
Liquid line restriction (% of system pressure drop)	0, 5, 10, 15, 20
Compressor valve leakage (% reduction in volumetric efficiency)	0, 7, 14, 21, 28
Condenser fouling (% blockage of face area)	0, 14, 28, 42, 56
Evaporator fouling (% loss of airflow rate)	0, 12, 24, 36

Classifying faults by their frequency of occurrence in leading to inadequate building comfort conditions showed that approximately 40% of the failures were electrical or controls related and the other 60% were mechanical. Classifying faults by the total service costs showed that compressor failures are by far the most costly failure for unitary air conditioners. Although most failures in hermetic compressors are diagnosed as a failure in the motor, it was found that these failures are usually the result of a mechanical problem that overloads the motor and leads to failure. The primary cause of mechanical failures in positive displacement compressors is liquid refrigerant in the compressor.

The transient test results showed that all the indices approached steady state within approximately 200 seconds after start-up for the conditions tested. Thus, fault detection and diagnostics could be performed for this type of equipment using methods that incorporate steady-state assumptions and models.

The measurements with the slowest transients are the air temperature rise across the condenser, the air temperature rise across the evaporator, the compressor outlet temperature, and the suction line superheat. The hot gas temperature, condensing temperature, cooling capacity, and air temperature difference appear to have first-order dynamics in response to the on/off cycling of the unit. The evaporation temperature, suction superheat, condenser subcooling, and the compressor power consumption exhibit higher-order dynamic behavior.

The impacts of the faults on performance indices were quantified. Refrigerant leakage, liquid-line restriction, and evaporator fouling have a greater effect on capacity than COP. Condenser fouling affects COP more than capacity, and compressor valve leakage affects both features about the same. Refrigerant leakage, liquid line restriction, and condenser fouling lead to higher compressor temperatures. Evaporator fouling, compressor valve leakage, and condenser fouling cause low suction superheat.

A set of rules for the FDD was derived from the test data and is summarized in the following table, where the + and – denote positive and negative residuals, respectively.

Table 4.4 FDD rules

Fault	T_{evap}	T_{sh}	T_{cond}	T_{sc}	T_{hg}	T_{ca}	T_{ea}
Refrigerant Leak	-	+	-	-	+	-	-
Compressor valve leakage	+	-	-	-	+	-	-
Liquid line restriction	-	+	-	+	+	-	-
Condenser fouling	+	-	+	-	+	+	-
Evaporator filter fouling	-	-	-	-	-	-	+

An analysis of fault significance and the data obtained in the study were used to design and evaluate the performance of an FDD method in the companion paper (Breuker and Braun, 1998b).

Breuker, M.S. and J.E. Braun, 1998, "Common Faults and their Impacts for Rooftop Air Conditioners," *International Journal of Heating, Ventilating, and Air Conditioning and Refrigerating Research*, Vol. 4, No. 3, pp. 303-318.

4.2.2 Vapor Compression Refrigerator Performance Degradation Due to Condenser Air Flow Blockage

Authors: D.H. Bultman, L.C. Burmeister, V. Bortone, and P.W. TenPas

Overview

The effect of partially blocked condensers of vapor compression equipment using R-22 was simulated. A model of a 3-ton refrigeration system was constructed by combining relatively simply models of the individual components, the refrigerant properties, and mass balances. The airflow rate was subsequently varied from 60% to 150% of the design rate in order to determine its effect on performance.

Components in the model included the compressor, throttling device, two heat exchangers, tubing, heat exchanger fans, and accumulator tank. Some simplifications in the modeling included: no pressure drops in the heat exchangers or tubing, the compressor's mechanical efficiency was assumed to be 100%, and the refrigerant quality varied linearly through the heat exchangers. The paper provides a thorough description of the model parameters used in the study.

In the worse case scenario studied in this paper, the COP was predicted to decrease by 7.6% when the airflow across the condenser was reduced by 40% for a constant speed fan. It is interesting to note that the net cooling capacity increased slightly during the first 20% reduction in airflow before beginning to decrease. The paper also meticulously describes all the time-based changes that occur in the system to produce a lower COP when the airflow rate is decreased.

Bultman, D.H., L.C. Burmeister, V. Bortone, and P.W. TenPas, 1993, "Vapor-compression refrigerator performance degradation due to condenser air flow blockage," *American Society of Mechanical Engineers (Paper)*, 93-HT-34, pp. 1-13.

4.2.3 Influence of the Expansion Device on Air-Conditioner System Performance Characteristics under a Range of Charging Conditions

Authors: M. Farzad and D.L. O'Neal

Overview

The main purpose of this paper was to describe a series of experiments concerned with the effects of off-design refrigerant charge and outdoor temperature on air conditioner system performance (capacity, EER, SEER, etc.). Although this paper does not address fault detection and diagnostics (FDD), the experiments and their results are important to FDD analysis and experimentation.

A nominal 3-ton-capacity, split system, residential air-conditioner was used in the experiments. The air-conditioner was placed in two psychrometric rooms that simulated indoor and outdoor conditions. Two different set-ups were used: one used capillary tubes as the expansion device and the other used a thermal expansion valve (TXV). The capillary tube system had four parallel capillary tubes and the indoor heat exchanger was a four-row, four-circuit, vertical coil. The TXV system consisted of a TXV rated at a three-ton capacity with a superheat of 11°F at the rating condition and the indoor heat exchanger was a three-row, four-circuit A-coil.

For the capillary tube, the superheat recommended by the manufacturer was used to set the charge in the system. For the TXV, a fixed subcooling temperature leaving the condenser was used for establishing the charge. Initially the charge was set at an outdoor temperature of 95°F and indoor conditions of 82°F dry-bulb and 67°F web-bulb. Refrigerant was added in one-ounce increments until the desired subcooling or superheat was reached. Subsequently, tests at this charge and at off-design charges from -20% to +20% (at 5% increments) were performed.

Four steady state tests in which dehumidification occurs on the evaporator coil were carried out. The first two were at the same indoor conditions (80°F dry-bulb and 67°F wet-bulb) and different outdoor temperatures (82°F and 95°F). The other two tests were done at two more outdoor temperatures (90°F dry-bulb and 100°F dry-bulb). Steady state and cyclic tests were also performed with no condensation on the evaporator coil. Both tests were performed with indoor conditions set at 80°F dry-bulb and 57°F wet-bulb and the outdoor condition was kept at 82°F and 20% RH.

The cooling cyclic test was conducted by cycling the compressor 6 minutes 'on' and 24 minutes 'off'. In addition to measurements made during the 'on' period, measurements of capacity were taken during the first two minutes of the 'off' period. For all tests, the psychrometric rooms used in this experiment were operated more than one hour in advance to ensure they were at the pre-set conditions when a test was initialized. Air side measurements were used to characterize the capacity of the various tests.

The results of the fully charged cases demonstrated that the total capacity, EER, and SEER decreased with increasing outdoor temperature for the fully charged case no matter what kind of expansion device was used. Furthermore, the unit with the TXV expansion device reached steady state after startup more rapidly than the system with the capillary tube expansion device.

The results of the off-design charged cases are divided according to whether the capillary tubes or the TXV were used.

Capillary Tube System Results

The capillary tube expansion system peaked in capacity at an 82°F outdoor temperature at full charge. When the outdoor temperature was increased, the peak shifted to those with lower charges. The drop in capacity for low-charge was steeper than for high-charge conditions at all outdoor temperatures, while at high-charge conditions the normalized capacity degraded more noticeably as the outdoor temperature increased.

One surprising result is that at low-charged cases, the capacity increased as the outdoor temperature increased. This stems from the higher refrigerant flow rate at higher outdoor temperatures.

Higher outdoor temperatures tend to decrease EER for a certain charging condition. As the outdoor temperature increased, the peak of EER shifted to lower charges. The drop in EER due to higher outdoor temperature at high-charge conditions was greater than that at low-charge conditions.

The paper utilized a variable, C_D (the coefficient of degradation), to measure the efficiency loss due to on/off cycling of the system (it was defined as such). With increasing refrigerant charge in the capillary system, the C_D dropped rapidly, which showed that the unit reached steady state more slowly with a high-charge than with a low-charge.

The normalized SEER had a distinct peak at full charge and decreased rapidly when the charge was higher or lower. This showed that the SEER of a capillary system had a strong dependence on refrigerant charge.

TXV System Results

The effect of the amount of refrigerant charge is relatively small for a system with a TXV as the expansion device compared with that of the capillary tube system. Results showed that the refrigerant flow rate was similar for all the charging tests, which explained why the capacity remained constant at different charging cases. (Normalized refrigerant flow rate kept increasing as the charge increased in capillary systems.)

The EER curves were approximately constant for charging conditions from -15% to +5% as the outdoor temperature increased. When charged at -20% and +20%, the EER dropped greatly when the outdoor temperature increased.

Normalized C_D for the TXV system varied little with the increasing refrigerant charge.

The SEER did not show as dramatic a drop as it had in the capillary system. The normalized SEER showed more degradation at high charge than at low charge.

Discussion

The paper shows that the capacity of TXV systems, compared to that of capillary systems, increases more quickly with the decrease of the outdoor temperature, and the power consumption decreases more slowly (see Figure 1 of paper). This could imply that a TXV system is more sensitive to outdoor temperature (and possibly fouling of the condenser).

The experiments during startup of the fully charged TXV and capillary tube system showed that the length of the startup transients was shorter for the TXV system than for the capillary system. This implies that for FDD methods using a steady state detector, it may be necessary to check if the steady state indicators in those FDD approaches (e.g., the hot gas temperature) still move toward steady state uniformly and slower than other measurements in the TXV system. The thresholds of the steady state detectors also need to be checked.

The information in this paper is quite meaningful for FDD in a capillary system.

- The experiments showed that if the outdoor temperature is too high, the peak of the capacity might shift to lower refrigerant charge, possibly making FDD more difficult or leading to wrong decisions in detecting the leakage of refrigerant at high outdoor temperature.
- At the same outdoor temperature, the drop of capacity caused by overcharge is much smoother than the drop when refrigerant charge decreases (refrigerant leakage). This might make the detection of overcharge more difficult than that of insufficient refrigerant charge.
- At some charge conditions, the influence of outdoor temperature on capacity is quite small, which may make the sensitivity of FDD in the detection of some faults, like the fouling of a condenser, to be less in this situation.

The experiments also showed that the capacity of the TXV system vs. charge is smoother and better behaved than that of the capillary system.

It seems that the capillary system takes more time to reach steady state at both higher and lower charge conditions. The variation is much less in the TXV system.

The variations of capillary, flow rate, EER, C_D and SEER of the TXV system with the changes of refrigerant charge and outdoor temperature are smaller and smoother than those of the capillary system. The effect of compensation in the TXV might make FDD more difficult and less sensitive. Also, the TXV causes the system to reach steady state more quickly after startup. Both of these facts may make it necessary to incorporate a method similar to the Start-Up Module presented by Stylianou (1996), which can detect some faults before the effect of the TXV becomes apparent.

Farzad, M. and D.L. O'Neal, 1993, "Influence of the Expansion Device on Air-Conditioning System Performance Characteristics Under a Range of Charging Conditions," *ASHRAE Transactions*, Vol. 99, Pt. 1, pp. 3-13.

4.2.4 Operating and Maintaining Rooftop Air Conditioners

Author: David Houghton

Overview

This paper recommended some maintenance steps for rooftop air conditioners in the field. Maintenance for twelve components is discussed.

1. Filters - The efficiency and cost of different types of filters are compared and pleated filters made with cotton or synthetic fabrics are recommended. The way to decide filter-changing intervals based on the pressure drop across the filter is discussed.
2. Evaporator coil - If the supply fan amperage and filter coil pressure drop is higher than last year's measurement, then the flow through the coil is lower and it needs to be cleaned.
3. Supply Fan - Maintenance for different types of bearings—sleeve bearings, self-lubricating bearings, and conventional greased ball bearings—are discussed. The cause of reversed fan operation and ways to prevent it are mentioned.
4. Fan Belt - Proper belt tension can be achieved with a deflection strain gauge or by pressing the belt. Its pays to prevent possible breakage with scheduled replacement.
5. Fan Motor – It's cost effective to specify premium-efficiency motors for rooftop units.
6. Outside Air dampers - A study of 13 rooftop units on small commercial buildings found that none of them had properly operating outside-air dampers, which shows that the problem with outside air-dampers is quite common. Damper servicing consists of cleaning, lubricating, and testing damper movement.
7. Cabinet Integrity
8. Refrigerant Charge - The author recommends that the most accurate way to check and correct refrigerant charge is by measuring superheat and/or subcooling. It was noted that superheat and subcooling measurements are meaningful only when correlated with the loads on the condenser and evaporator. Furthermore, some manufacturers now specify superheat measured at the suction line entrance to the compressor, which results in a several degree difference in measurement compared to the traditional measurement done at the expansion valve bulb.
9. Expansion Valve - The valve's sensing bulb should be attached to the suction line with copper straps rather than steel hose clamps or plastic zip-ties.
10. Compressor - Ninety percent of rooftop unit replacements are because of failure in the hermetic motor-compressor. Electrical testing, oil testing and voltage problems are discussed.
11. Condenser Coil - Cleaning the condenser with a power washer is recommended.
12. Condenser Fan and Motor - A healthy deadband (20 to 50 psi) between cut-in and cut-out pressure set points was recommended to prevent rapid condenser fan cycling.

Houghton, D., 1997, "Operating and Maintaining Rooftop Air Conditioners", *ASHRAE Journal*, Vol. 39, December, pp. 50-54.

4.2.5 Air Conditioning and Heat Pump Operating Cost Savings by Maintaining Coil Cleanliness

Authors: B.C. Krafthefer, D.R. Rask, and U. Bonne

Overview

The paper seeks to demonstrate the cost effectiveness of using high efficiency air cleaners (HEAC) instead of more commonly used dust stop filters in heat pumps. Studies have shown that finned-tube coils capture and retain a large portion of particulate matter. This in turn leads to decreased heat exchanger efficiency as the unit gets older. The study was conducted using climate data from the southeastern U.S.

The authors first performed simulations that showed an average savings of 10 to 25% over a 15-year service life (25 to 55% during the 15th year). The authors also performed some experimental testing that proved inconclusive and inconsistent, but still contained some trends which support their claims. One of the drawbacks of the experimental testing was that the airflow rates were kept constant despite the reduction that would occur in field units. Consequently, an experiment was performed with a 50% reduction in airflow, resulting in an 11.5 to 13.2% drop in COP. The authors note that they have only considered finned-tube coils in heat pump evaporators.

Krafthefer, B.C. Rask, and D.R. Bonne, 1987, "Air-conditioning and heat pump operating cost savings by maintaining coil cleanliness," *ASHRAE Transactions*, Vol. 93, Pt. 1, pp. 1458-1473.

4.2.6 Failure Diagnosis for a Household Refrigerator

Author: Michael G. McKellar

Overview

A household refrigerator was studied with the following failures:

1. Partially blocked capillary tube
2. Failed condenser fan
3. Failed evaporator fan
4. Leaking compressor (piston or suction valve leak)
5. Frost on evaporator
6. Refrigerant undercharge
7. Refrigerant overcharge

Failures could be detected by observing the high and low side pressures and their ratio. Appropriately placed thermocouples can be used to find the pressure according to saturated state conditions. Furthermore, a polytropic relationship between the compressor temperature and pressure ratios is used to account for superheat into the evaporator during certain failures.

The research objectives were:

- Identifying the most significant failures
- Testing the refrigerator to observe the characteristics of each failure
- Determine which sensors provide the most information about the failures
- Develop a mathematical model and computer model of the refrigerator and simulate the failures

According to a major appliance company, 77.1% of refrigerator defects are related to the compressor and 11.4% are related to a leak in one of the components.

Measurements were collected from 66 thermocouples, 5 pressure transducers, 3 flow meters, a wattmeter, and torque meter. The main features of the collected information on the compressor were the suction pressure, suction temperature, discharge pressure, discharge temperature, electrical power, slip rpm of motor, work, and heat transfer. The heat exchanger transducers provided information on the inlet and outlet pressures and temperatures of the refrigerant; the refrigerant pressure drop; inlet and outlet temperatures of the air; regions of superheat, saturation, and subcooling; and heat transfer. The following information was measured from the capillary tube: inlet and outlet pressures and temperatures, heat transfer to the return line, pressure drop, and pressure drop due to a blocked line.

Placing a ball valve before the capillary tube simulated the partially blocked capillary tube. It caused liquid refrigerant to accumulate in the condenser, reduced the mass flow rate, lowered the evaporator temperature, and the refrigerant entering the evaporator was superheated.

Cutting the power supply to the condenser fan simulated the condenser fan failure. The effects include a higher condensing pressure, increased compressor power, and equal air temperatures across the condenser.

Cutting the power supply to the evaporator fan simulated the evaporator fan failure. The characteristics of this failure were lower pressures throughout the system, but the pressure ratio between the low and high side increased.

The compressor leak was simulated using a bypass line. The failure manifested itself through a higher low side pressure and a lower high side pressure, thus reducing the pressure ratio.

Introducing frost on the evaporator created the same trends as having the evaporator fan off, except to a lesser degree.

Refrigerant undercharge resulted in lower pressures throughout the system, a decrease in the pressure ratio, and refrigerant entered the evaporator superheated. Refrigerant overcharge caused higher pressures throughout the system, greater heat transfer in the evaporator and condenser, and higher mass flow rate and power input.

The model of the system consists of two parts. The first part contains the refrigeration equipment: the compressor, the condenser, the capillary tube, and the evaporator. The second is a lumped capacitance model of the freezer and fresh food cabinets. Steady state conditions were assumed for the refrigerant systems, whereas the cabinet temperatures used a lumped parameter transient system.

The computer model simulated heat transfer during normal conditions to within 1% and the mass flow rate to within 4%. However, some significant deviations were encountered between the computer model and the measured data during the various fault simulations.

McKellar, M.G., M.S., 1987, “Failure Diagnosis for a Household Refrigerator,” Master Thesis, School of Mechanical Engineering, Purdue University.

4.2.7 Minimizing Operating Costs of Vapor Compression Equipment with Optimal Service Scheduling

Authors: Todd M. Rossi and James E. Braun

Overview

The paper evaluated the maximum cost savings associated with using optimal service scheduling for the cleaning of heat exchangers in packaged air-conditioning equipment and developed a more practical, near optimal scheduling technique for practical use. It demonstrated that there is a significant opportunity for cost savings associated with optimal scheduling of condenser and evaporator maintenance by comparing it with results for regular service intervals and service dictated only by violation of the constraints.

Maintenance scheduling was determined using the fault evaluation criteria described below:

- Economic criteria. Service is required when it contributes to the reduction of the combined costs of energy and service over the lifetime of the unit.
- Comfort or refrigeration set point criteria
- Safety criteria
- Environmental criteria
-

However, only condenser and evaporator fouling were considered in this paper.

To develop the optimal maintenance scheduler, several assumptions were made:

- The comfort, premature wear, and liability costs are much larger than the service cost to repair them.
- The available opportunities to perform service are limited to periodic occurrence.
- The service schedule eventually settles into a cycle.
- Typical meteorological year weather data were used and the typical year's weather patterns were assumed to reoccur each year.

Given a model for determining the power consumption rate, the service to energy cost ratio and the minimum service interval, the optimization problem is defined as minimizing the cost with respect to:

- The length of the service cycle after which the service scheduling repeats, T_c,
- The total number of services in one service cycle, N_c,
- The time of the first service task in the schedule, t_1,
- A vector of time periods between service tasks within the service cycle.

The numerical solution to the optimization problem was accomplished using two numerical techniques. First, given values of $[T_C, N_C, t_1]$, the optimal set of time periods between service tasks was determined using dynamic programming. Second, an outer loop containing the dynamic programming solution was then used to find the values of $[T_C, N_C, t_1]$.

With regular maintenance scheduling, preventive maintenance is performed at regular time intervals. When the chosen interval is not sufficient to maintain the constraints on comfort and safety, the costs associated with the schedule are set artificially high. The constrained service scheduler only performs service when a comfort or equipment safety constraint is violated.

The optimal service schedule was simplified based on the following simplifications:

- The time between service tasks was fixed
- The cost was only a function of the runtime since the last service
- The energy cost (with no performance degradations) associated with seasonal effects was subtracted from the total cost.

Simulations were used to demonstrate the potential for optimal service scheduling and to evaluate the performance of the simplified near-optimal service scheduler. It was found that optimal service scheduling reduced lifetime operating costs for a rooftop air-conditioner by as much as a factor of two over regular service intervals, and 50% when compared to constrained only service. The near-optimal algorithm gave operating costs that were within 1% of the optimal results.

Rossi, T.M. and J.E. Braun, 1996, "Minimizing Operating Costs of Vapor Compression Equipment with Optimal Service Scheduling," *International Journal of Heating, Ventilating, and Air Conditioning and Refrigerating Research*, Vol. 2, No. 1, pp. 3-26.

4.3 Other HVAC System and Subsystem Applications

4.3.1 Diagnostics for Outdoor Air Ventilation and Economizers

Authors: Michael Brambley, Robert Pratt, David Chassin, Srinivas Katipamula and Darrel Hatley

Overview

The paper introduces a tool known as the outdoor air economizer (OAE) diagnostician that automates detection and diagnosis of problems associated with outdoor-air ventilation and economizer operation.

The current prototype of the OAE diagnostician works on constant-volume systems and variable air volume (VAV) systems that do not use volume compensation. "The tool diagnoses the operating conditions of AHUs using rules derived from engineering models of proper and improper air-handler performance. These rules are implemented in a decision tree structure in software."

The diagnostician is configured for each specific air handling unit (AHU) and its control during setup. During operation, data collected by the building automation system (BAS) is stored and utilized in batch mode or in (near) real-time mode.

The current prototype could detect about 20 different basic operation problems, which are associated with inaccurate outside air, wrong economizer operating, control or sensor problems, and incorrect setup of the diagnostician. However, no detailed description of the algorithm was given.

The diagnostician uses color-coding to alert when problems occur and provides assistance in identifying the cause of the problem. Occasionally, several causes may be presented and the operator must inspect the unit to identify the correct one.

The OAE diagnostician was installed and operated with AHUs in two buildings. For each AHU, data was recorded hourly from BAS sensors using a DDE connection for outside air temperature, return air temperature, mixed air temperature, supply air temperature, on/off status of the supply fan, and open/closed status of the chilled water and hot water valves.

Of the seven air handlers monitored, some were found to have problems shortly after initial processing of the data. All the problems found, such as with the outdoor air sensor and faulty operation of the economizer, have been confirmed by the inspection of the AHUs. Therefore, the OAE diagnostician has proven effective in identifying installation and operation problems in AHUs during initial field testing.

Method Assessment

Although the description in this paper is quite general, the interface of the software is quite good and worth learning.

Brambley, M., R. Pratt, D. Chassin, S. Katipamula, and D. Hatley, 1998, "Diagnostics for Outdoor Air Ventilation and Economizers," ASHRAE Journal, Vol. 40, October, pp. 49-55.

4.3.2 Expert Systems in Preventive Maintenance and Diagnostics

Author: Charles H. Culp

Overview

This paper presents the use of an expert system contained within a portable computer that can be used by a mechanic to diagnose problems in an HVAC system.

Functions needed in an expert system for maintenance includes:

1. Configuration ability – to handle different manufacturer models and operating conditions.
2. Site Visit Types – the extent to which maintenance is to be performed (ranging from gauge check to complete teardown).
3. User Interaction – will ask user questions that can be quickly answered.
4. Explanations – ability to explain why a certain action was taken.
5. Graphics – useful in showing how an item should look or where it is located.
6. Context Sensitivity – guides the user to do various checks based on the machine's past history.
7. Display readings – particularly the most recently entered values.
8. Log Conditions – save measurements and activity for use during subsequent visits.
9. Defer Work – ability to put off maintenance till later if the part is not available.
10. Reports – document what was found and what was done.
11. Comments – information peculiar to a specific site.
12. Display – ability to see various features simultaneously.

The author presents a sample site visit with the mechanic's inputs to the expert system. At one point the condenser pressure is noted as being high with the possible causes being: tube fouling, air in condenser water, non-condensables in refrigerant, or excessive flow through condenser.

Culp, C., 1989, “Expert Systems in Preventative Maintenance and Diagnostics,” *ASHRAE Journal*, Vol. 31, No. 8, pp. 25-27.

4.3.3 Air Conditioning and Refrigeration Equipment Failures

Authors: David E. Stouppe and Tom Y. S. Lau

Overview

The article uses eight years of data comprising 15,760 failures. 11,349 of the failures were electrical, involving motors, controls and electrical apparatus; 4,411 failures were mechanical, involving compressors, system piping, or vessels. 12,518 of these failures were selected for further study; the others were either isolated events or had an undetermined cause.

For large hermetic compressors and motors the average age of motor failure is 10 years. If mechanical damage to the compressor occurs, the likely age is 15 years for a centrifugal compressor, and about 11 years for reciprocating compressors.

For large non-hermetic compressors and motors the average age of motor failure is 12 years. If mechanical damage to the compressor occurs, the likely age is 12 years for a centrifugal compressor, and about 16 years for reciprocating compressors.

In hermetic air conditioning and refrigeration units, 76.6% of the failures were electrical, 18.9% were mechanical, and 4.5% were refrigerant circuit.

Unbalanced voltage in a 3-phase motor leads to overheating. A 3% voltage imbalance results in approximately a 25% increase in the temperature of the windings.

Liquid slugging led to 20% of all mechanical failures in reciprocating compressors. This is usually avoided by using crankcase heaters to heat the oil and keep the refrigerant as a vapor, thus preventing refrigerant migration to the crankcase.

The most common failure of centrifugal compressors is loss of bearing lubrication, resulting in 55% of the failures in hermetic compressors and 69% of the failures in non-hermetic compressors.

Stouppe, D.E. and Y.S. Lau, 1989, “Air Conditioning and Refrigeration Equipment Failures,” *National Engineer*, Vol. 93, No. 9, pp. 14-17.

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